# Fault diagnosis method of pitch actuators for wind turbines based on variable forgetting factor identification algorithm

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**Abstract**

To diagnose the fault in pitch actuator of wind turbines, a fault diagnosis method is proposed in this paper, which is based on the variable forgetting factor recursive least-squares algorithm. According to the characteristic that the system parameters are changed by faults, the VFF-RLS system identification algorithm is adopted to estimate the changing parameters. The fault diagnosis problem is transformed into a parameter estimation issue. Then the time-varying natural frequency and damping ratio of pitch actuators are estimated based on the discrete model. The convergence rate and identification accuracy of the identification algorithm can be guaranteed by adjusting the forgetting factor automatically. The simulation results validate the effectiveness of the proposed method.

**Keywords: wind turbines; pitch actuator; fault diagnosis; system identification; variable forgetting factor**

## 1 Introduction

As the fastest growing renewable energy, the wind energy has raised the world's attention [1]. But wind farms are generally built in adverse conditions such as desert or sea areas [2], which may cause severe failures. The hydraulic pitch systems adjusts the pitch angle for constant power output, while wind speed is higher than the rated value, is an important component of the pitch wind turbine [3]. Once it fails, it directly affects the system stability, so accurate fault diagnosis for pitch wind turbine is essential.

Hydraulic pitch system fault diagnosis method is broadly divided into two categories, which is based on the data-driven, the model and the data-driven approach, Crowther uses neural networks for fault diagnosis of the hydraulic system [4]. Goharrizi uses Hilbert transform on fault detection of hydraulic actuator hydraulic leaks [5].

Goharrizi uses the fast Fourier transform and Wavelet transform method for detection of actuator hydraulic leaks [6]. However, the data-driven based approach often requires a lot of prior knowledge about the failure characteristics. Model-based methods without prior knowledge, has got more attention and development [7]. For the wind turbine pitch system, Wei uses the filter and observer to diagnose pitch actuator fault [8]. Wu uses the adaptive parameter estimation algorithm which is based on dynamic model of hydraulic pitch system, to detect the pitch system hydraulic pressure leakage fault [9].

The system identification method uses the system's input and output data to estimate parameters [10]. When hydraulic pitch system fails, some parameters of the pitch change, system identification methods can

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be used to estimate the change of data, and the fault diagnosis problem can be converted to the parameter estimation [11]. Faulty pitch systems can be modeled as a time-varying system, and a forgetting factor is introduced to estimates the time-varying system effectively. But identification methods of time-varying parameter with forgetting factor cannot achieve satisfactory result. While the forgetting factor is large, the algorithm converges slowly, while the forgetting factor is small, the algorithm produces large estimation errors [12]. Identification algorithm with variable forgetting factor can automatically choose a appropriate forgotten factor, to achieve high convergence speed and accuracy [13]. Therefore, this paper utilizes the variable forgetting factor recursive least squares (VFF-RLS) identification algorithms to estimate parameters of pitch system, the estimated values are compared with theoretical value to detect faults and identify the fault type.

# 2 Model Description

## 2.1 Wind Turbine Model

The wind turbine system includes the aerodynamic subsystem, the pitch subsystem, the drive train subsystem and the power subsystem. Among them, the power subsystem is consisted of the generator and converter. The interconnected relationship of various subsystem is shown in Fig. 1 [14].

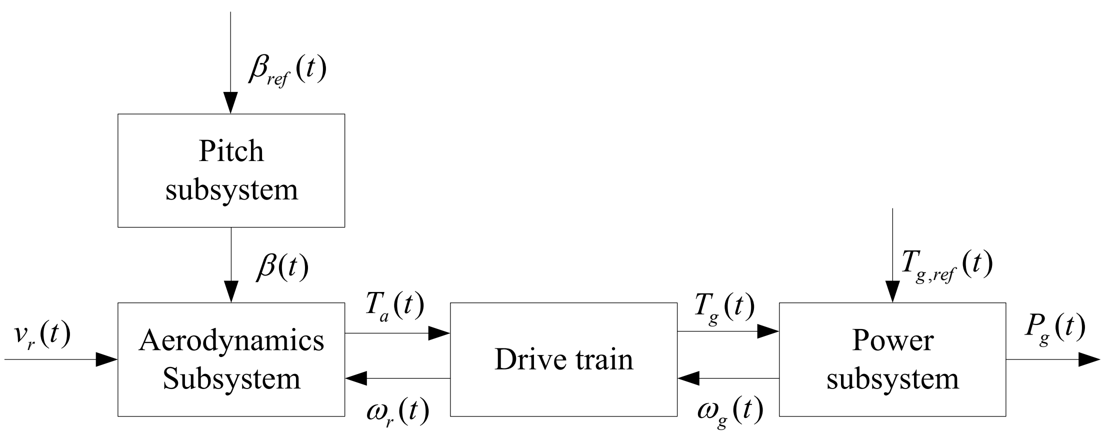


Figure 1: The structure of the wind turbine system model

The aerodynamic subsystem produces aerodynamic torque under the action of the effective wind speed $v_r(t)$, the rotor speed $\omega_r(t)$ and the pitch angle $\beta(t)$. The drive train subsystem transmits the rotor speed $\omega_r(t)$ to the generator speed $\omega_g(t)$. The electrical power generated by the converter is connected to the public power grid. For variable pitch wind turbines, in order to meet the operational requirements of the variable speed variable pitch, blade pitch angle $\beta(t)$ and torque $T_g(t)$ are adjusted according to the reference value $\beta_{ref}(t)$ and $T_{g,ref}(t)$. The pitch angle $\beta(t)$ is controlled by the pitch system, and the torque $T_g(t)$ is controlled by the converter.

## 2.2 Pitch and Fault Model

The wind turbine hydraulic pitch system schematic is shown in Fig. 2, it contains: 1. the hydraulic pump, 2. the hydraulic tank, 3. the proportioning valve, 4. the safety valve, 5. the hydraulic actuator and 6. the slider-crank mechanism. The crank-slider mechanism is used to connect the pitch by pitch actuators, the pitch angle is adjusted by rotating blades.

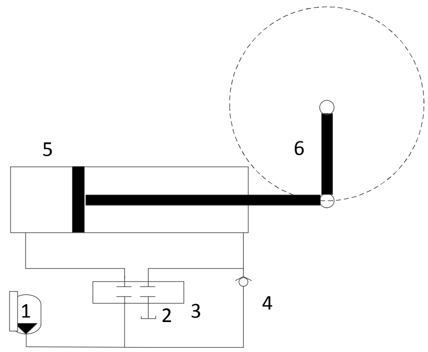


Figure 2: The hydraulic pitching system

The hydraulic pitch actuator can be modeled as a second order system [15], the dynamic model is

$$\ddot{\beta}(t) = -2\zeta\omega_n\dot{\beta}(t) - \omega_n^2\beta(t) + \omega_n^2\beta_{ref}(t), \tag{1}$$

where $\omega_n$ is the natural frequency of actuator, $\zeta$ is the damping ratio. of the actuator.

This paper focuses on the following pitch faults, the high air content in the hydraulic oil, the hydraulic leakage and the pump wear. Faults affect the dynamic properties of the system by changing the natural frequency and the damping coefficient. Under the influence of the fault, the natural frequency and the damping coefficient changes from the nominal value $\omega_{n,0}$ and $\zeta_0$to three kinds of parameter values, which is $\omega_{n,ha}$ and $\zeta_{ha}$, $\omega_{n,hl}$ and $\zeta_{hl}$, $\omega_{n,pw}$ and $\zeta_{pw}$.

The dynamic model of the pitch system with fault is

$$\ddot{\beta}(t) = -2\zeta(t)\omega_n(t)\dot{\beta}(t) - \omega_n^2(t)\beta(t) + \omega_n^2(t)\beta_{ref}(t), \tag{2}$$

where $\zeta(t)$ and $\omega_n(t)$ have different values under different faults, the specific expression is

$$\begin{aligned}
\omega_n(t) &= (1-\eta_{ha}(t))\omega_{n,0} + \eta_{ha}(t)\omega_{n,ha}, && (3)\\
\zeta(t) &= (1-\eta_{ha}(t))\zeta_0 + \eta_{ha}(t)\zeta_{ha}, && (4)\\
\omega_n(t) &= (1-\eta_{hl}(t))\omega_{n,0} + \eta_{hl}(t)\omega_{n,hl}, && (5)\\
\zeta(t) &= (1-\eta_{hl}(t))\zeta_0 + \eta_{hl}(t)\zeta_{hl}, && (6)\\
\omega_n(t) &= (1-\eta_{pw}(t))\omega_{n,0} + \eta_{ha}(t)\omega_{n,pw}, && (7)\\
\zeta(t) &= (1-\eta_{pw}(t))\zeta_0 + \eta_{ha}(t)\zeta_{pw}, && (8)
\end{aligned}$$

where $\eta_{ha}(t)$, $\eta_{hl}(t)$ and $\eta_{pw}(t)$ are the indicator of the high air content in the hydraulic oil, the hydraulic leakage and the pump wear, and $0 \le \eta_{ha}(t) \le 1, 0 \le \eta_{hl}(t) \le 1, 0 \le \eta_{pw}(t) \le 1$.

# 3 Fault Diagnosis Method Based on VFF-RLS

## 3.1 Structure of the Fault Diagnosis System

Based on the pitch actuator fault model, the VFF-RLS algorithm is used to diagnose faults. Fault diagnosis method needs the input and output data of the pitch system. The method take the pitch angle reference $\beta_{ref}(t)$ as the input of the algorithm, and the actual pitch angle as the output of the algorithm. The pitch actuator parameters $\omega_n(t)$ and $\zeta(t)$ can be estimated through the VFF-RLS algorithm.

From the Eq.(3) to Eq.(8), the natural frequency $\omega_n(t)$ and the damping coefficient $\zeta(t)$ of each kind of fault have the corresponding curve with the signal $\eta(t)$. It is assumed in this paper that two or more faults will not occur simultaneously, the identification estimates two parameter values on their respective curves, when $\eta(t)$ is greater than a certain threshold, it indicates a fault has occurred. Then, according to estimated values $\omega_n(t)$ and $\zeta(t)$ the corresponding curve is determined, thereby the distinguish of the fault type can be completed. The structure of fault diagnosis is shown in Fig. 3.

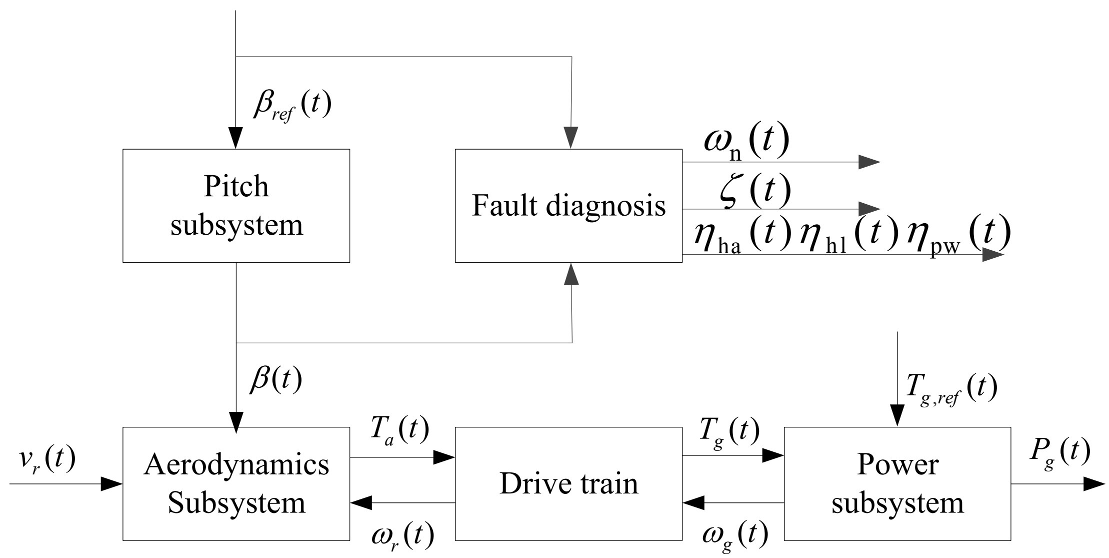


Figure 3: The structure chart for fault diagnosis

### 3.2 Discrete Model

The system identification algorithm must be implemented by a computer program, so the model needs to be discretization from the continuous system model, and eventually be converted into the corresponding difference equation.

First of all, for the pitch system with fault depicted in Eq.(2), $x(t) = [\beta(t), \dot{\beta(t)}]^{\mathrm{T}}$ is chosen as the state variables, $y(t) = \beta(t)$ is chosen as the output, its normative state space equation for the continuous system is

$$\begin{cases} \dot{x}(t) = & \bar{A}x(t) + \bar{B}u(t) \\ y(t) = & \bar{C}x(t) \end{cases}, \tag{9}$$

where $\bar{A} = \begin{bmatrix} 0 & 1 \\ -\omega_n^2(t) & -2\zeta(t)\omega_n(t) \end{bmatrix}^{\mathrm{T}}$, $\bar{B} = \begin{bmatrix} 0 & \omega_n^2(t) \end{bmatrix}^{\mathrm{T}}$, $\bar{C} = \begin{bmatrix} 1 & 0 \end{bmatrix}$.

Then, the discrete model is obtained from the continuous-time state equation. The impulse invariant transformation method is commonly used discretization, which can ensure the output of the discrete model is equal to output of the continuous-time system at certain sample points [16]. Take the sampling period as $T_0$, when the period is small, the $u(t)$ can be considered unchanged during one sampling period, that is $u(t) = u(kT_0), kT_0 \leq t < (k+1)T_0$. We denote $x(kT_0) =: x(k), u(kT_0) =: u(k), y(kT_0) := y(k)$, then the discrete model from Eq.(9) is

$$\begin{cases} x(k+1) = & Ax(k) + Bu(k) \\ y(k) = & Cx(k) \end{cases}, \tag{10}$$

where $A = e^{\bar{A}T_0} \approx I + \bar{A}T_0 = \begin{bmatrix} 1 & T_0 \\ -\omega_n^2(k)T_0 & 1-2\zeta(k)\omega_n(k)T_0 \end{bmatrix}$, $B = \left[\int e^{\bar{A}(T_0-t)}dt\right]\bar{B} = \bar{B}T_0 = \begin{bmatrix} 0 & \omega_n^2(k)T_0 \end{bmatrix}^{\mathrm{T}}$, $C = \bar{C} = \begin{bmatrix} 1 & 0 \end{bmatrix}$.

### 3.3 Analysis of the System Parameter's identifiablity

System identification methods can only be used in the identifiable system. As this paper identifies changing parameters of the system, it is necessary to determine whether the system is a parameter identifiable system. According to the Eq.(10), the controllability matrix of the system is $Q_e = \begin{bmatrix} B & AB \end{bmatrix} = \begin{bmatrix} 0 & \omega_n^2(k)T_0^2 \\ \omega_n^2(k) & (1-2\zeta(k)\omega_n(k)T_0)\omega_n^2(k)T_0 \end{bmatrix}$, $rankQ_e = 2$, the controllability matrix is full rank, so the system can be controlled. The system observability matrix is

$$Q_o = \begin{bmatrix} C \\ CA \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 1 & T_0 \end{bmatrix}$$

, $rankQ_o = 2$, the observability matrix is full rank, so the system can be observed. From the above analysis, this system is a identifiable.

The system's input and output expressions are

$$\begin{aligned} y(k) &= C(zI-A)^{-1}Bu(k) \\ &= b_2(k)z^{-2}u(k)/1 + a_1(k)z^{-1} + a_2(k)z^{-2} \end{aligned} \tag{11}$$

where $a_1(k), a_2(k)$ and $b_2(k)$ are

$$a_1(k) = 2\zeta(k)\omega_n(k)T_0 - 2 \tag{12}$$

$$a_2(k) = \omega_n^2(k)T_0^2 + 1 - 2\zeta(k)\omega_n(k)T_0 \tag{13}$$

$$b_2(k) = \omega_n^2(k)T_0^2 \tag{14}$$

Eq.(11) can be written as a differential equation

$$\begin{aligned} y(k) + a_1(k)y(k-1) + a_2(k)y(k-2) = \\ b_2(k)u(k-2) + v(k) \end{aligned} \tag{15}$$

The system identification algorithm is able to estimate the coefficients $a_1(k)$, $a_2(k)$ and $b_2(k)$. The time-varying parameters $\zeta$ and $\omega_n(k)$ can be obtained from the Eq.(12) to Eq.(14), and the system Eq.(10) is parameter identifiable. Therefore, system identification methods can be used to estimate the wind turbine system.

### 3.4 Fault Diagnosis Algorithm

The VFF-RLS algorithm is based on the identification model, which consisted of the discrete systems Eq.(10) and the differential equation Eq.(15),

$$y(k) = \varphi^{\mathrm{T}}(k)\theta + v(k) \tag{16}$$

where $\varphi(k) = \begin{bmatrix} -y(k-1) & -y(k-2) & -u(k-2) \end{bmatrix}^{\mathrm{T}}$ is the information vector, $\theta(k) = \begin{bmatrix} a_1(k) & a_2(k) & b_2(k) \end{bmatrix}^{\mathrm{T}}$ is the parameters to be estimated, $v(k)$ is the white noise with zero mean.

The estimated value of the identification model Eq.(16) can be obtained from VFF-RLS algorithm defined by the following equation,

$$d(k) = y(k) - \varphi^{\mathrm{T}}(k)\hat{\theta}(k-1), \tag{17}$$

$$L(k) = \frac{P(k-1)\varphi(k)}{\lambda(k) + \varphi^{\mathrm{T}}(k)P(k-1)\varphi(k)}, \tag{18}$$

$$\hat{\theta}(k) = \hat{\theta}(k-1) + L(k)d(k), \tag{19}$$

$$P(k) = \frac{1}{\lambda(k)}[P(k-1) - L(k)\varphi^{\mathrm{T}}(k)P(k-1)], \tag{20}$$

where $\lambda(k)$ is the variable forgetting factor, $L(k)$ is the gain matrix, $P(k)$ is the covariance matrix.

As the $k-1$ estimator is used by the parameter $d(k)$ of the Eq.(17), it is a priori error. The posteriori error is defined as

$$\mu(k) = y(k) - \varphi^{\mathrm{T}}(k)\hat{\theta}(k) \tag{21}$$

combined with the Eq.(17), Eq.(18) and Eq.(19), the Eq.(21) can be converted to

$$\mu(k) = d(k)\left[1 - \frac{\varphi^{\mathrm{T}}(k)P(k-1)\varphi(k)}{\lambda(k)+\varphi^{\mathrm{T}}P(k-1)\varphi k}]\right], \tag{22}$$

we denote $h(k) = \varphi^{\mathrm{T}}P(k-1)\varphi(k)$, so

$$\mu(k) = d(k)\left[1 - \frac{h(k)}{\lambda(k)+h(k)}\right]. \tag{23}$$

The variance of the system noise $v(k)$ is $\sigma$, a posteriori error covariance is approximately equal to the noise variance, that is $E[\mu^2(k)] = \sigma_v^2(k)$, $E$ is the expectation operator. Combined with Eq.(23),

$$E\left\{d^2(k)\left[1 - \frac{h(k)}{\lambda(k)+h(k)}\right]^2\right\} = \sigma_v^2(k), \tag{24}$$

where $E[d^2(k)] = \sigma_d^2(k), E[h^2(k)] = \sigma_v^2(k)$.

However, the variance $\sigma_v^2(k)$, $\sigma_d^2(k)$ and $\sigma_h^2(k)$ is difficult to get an accurate value, the $\hat{\sigma}_v^2(k)$, $\hat{\sigma}_d^2(k)$ and $\hat{\sigma}_h^2(k)$ can be obtained based on the estimated variance in length of the data collected, which are

$$\hat{\sigma}_v^2(k) = \frac{1}{k}\sum_{j=1}^{k}[y(j) - \varphi^{\mathrm{T}}(j)\hat{\theta}(j)]^2 \tag{25}$$

$$\hat{\sigma}_d^2(k) = \frac{1}{k}\sum_{j=1}^{k}[y(j) - \varphi^{\mathrm{T}}(j)\hat{\theta}(j-1)]^2 \tag{26}$$

$$\hat{\sigma}_h^2(k) = \frac{1}{k}\sum_{j=1}^{k}[\varphi^{\mathrm{T}}(j)P(j-1)\varphi(j)]^2 \tag{27}$$

By solving the Eq.(24), the variable forgetting factor $\lambda(k)$ is

$$\lambda(k) = \frac{\sigma_h(k)\sigma_v(k)}{\sigma_d(k) - \sigma_v(k)} \tag{28}$$

As the forgotten factor $\lambda$ is greater than zero, in Eq.(28), $\sigma_d(k) \geq \sigma_v(k)$. It is obviously when $\hat{\sigma}_d(k) \leq \hat{\sigma}_v(k)$, we can set $\lambda(k) = \lambda_{min}$. However, when the algorithm is in a stable state, the value of $\hat{\sigma}_d(k)$ fluctuate around the value of $\hat{\sigma}_v(k)$, this limits the above setting method. More appropriate approach needs to be chosen, that is when $\hat{\sigma}_d(k) \leq \gamma\hat{\sigma}_v(k)(1 < \gamma < 2)$, sets $\lambda(k) = \lambda_{min}$, $\lambda_{min}$ is taken as a value which is close or equal to 1. Otherwise, the forgetting factor of the VFF-RLS algorithm will automatically adjusted to

$$\lambda(k) = min\left\{\frac{\sigma_h(k)\sigma_v(k)}{\xi + \sigma_d(k) - \sigma_v(k)}, \lambda_{max}\right\}. \quad (29)$$

In order to prevent the denominator to be zero, $\xi$ in Eq.(29) is taken as the minimum value, and the $\xi$ is the minimum positive constant. When the system changes, $\hat{\sigma}_d(k)$ is significantly greater than $\hat{\sigma}_v(k)$, the forgetting factor $\lambda$ in Eq.(29) is automatically switched to the smaller value to increase the convergence speed. When the algorithm tends to converge into a stable state, the $\hat{\sigma}_d^2(k) \cong \hat{\sigma}_v^2(k)$, and meet $\hat{\sigma}_d(k) \leq \hat{\sigma}_v(k)$, $\lambda(k)$ should become $\lambda_{max}$ to reduce estimate errors and improve identification accuracy.

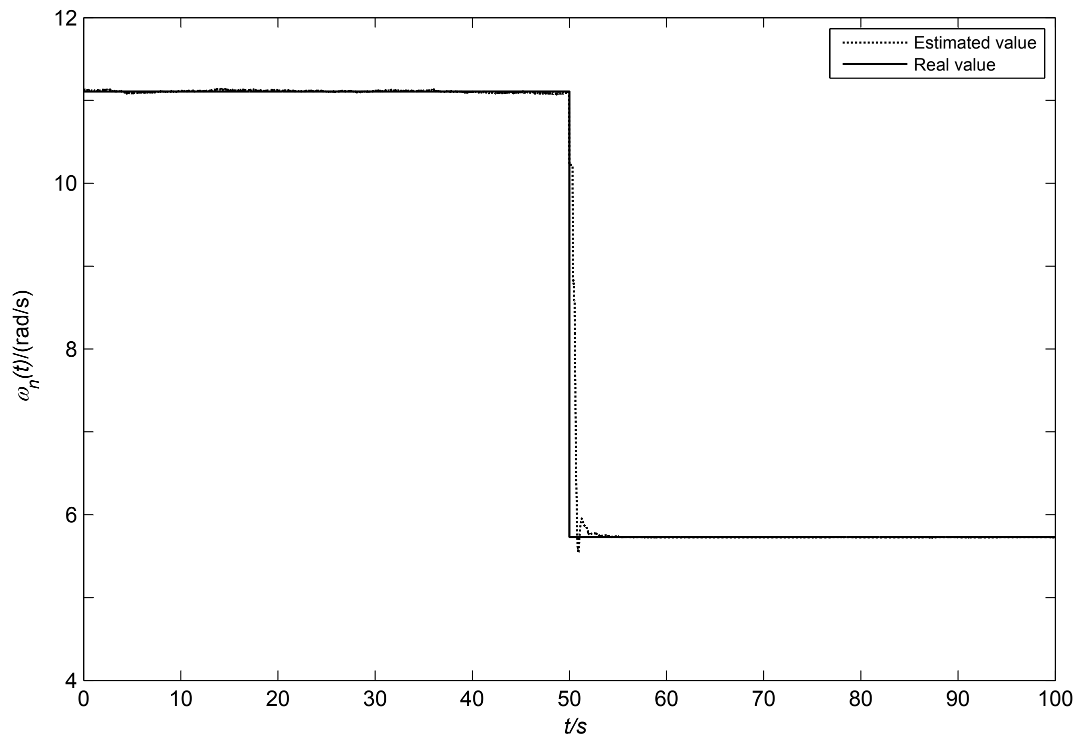


Figure 4: The parameter $\omega_n(t)$ of the high air content in the hydraulic oil

# 4 Simulation

The simulation is based on the 4.8MW wind turbine benchmark model [17], the fault diagnosis system shown in Fig. 3, and the VFF-RLS algorithm described in section 3.2. When impulse invariant transformation

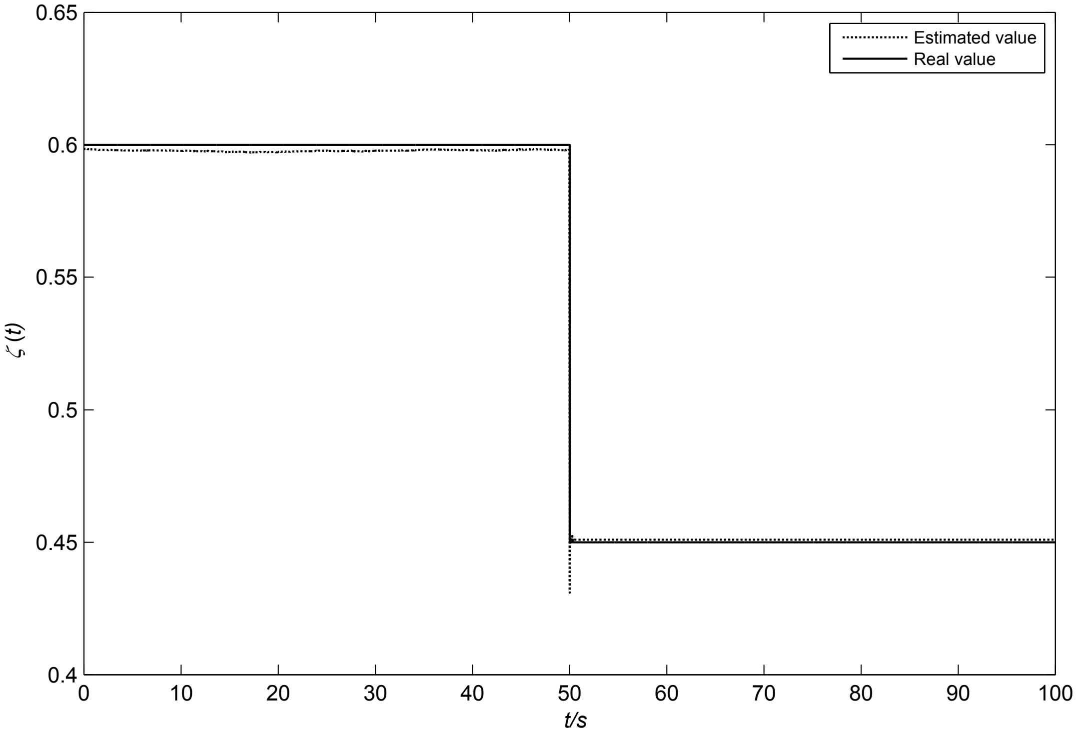


Figure 5: The parameter $\zeta(t)$ of the high air content in the hydraulic oil

method is used in the discretization of the system, we can denote $u(t) = u(kT_0) =: u(k)$. Therefore, the variable forgetting factor is $\lambda(t) = \lambda(kT_0) =: \lambda(k)$, the time-varying parameters are $\zeta(t) = \zeta(kT_0) =: \zeta(k)$ and $\omega(t) = \omega(kT_0) =: \omega(k)$.

There are three wind turbine pitch actuator faults discussed in this paper, which are high air content in the hydraulic oil, hydraulic leakage and pump wear. It is assumed that two or more faults will not occur simultaneously, and three kinds of single fault are simulated respectively. The parameters are shown in Tab. 4. In simulation, the fault is supposed to happen at 50s, the fault indicator signal is

$$\eta_{ha}(t), \eta_{hl}(t), \eta_{pw}(t) = \begin{cases} 0, 0s \leq t \leq 50s \\ 1, 50s < t \leq 100s \end{cases} \tag{30}$$

Table 1  Parameters' value

| Fault type | Value |
|---|---|
| No fault | $\omega_{n,0} = 11.11rad/s, \zeta_0 = 0.6$ |
| High air content in hydraulic oil | $\omega_{n,ha} = 5.73rad/s, \zeta_{ha} = 0.45$ |
| Hydraulic leakage | $\omega_{n,hl} = 3.42rad/s, \zeta_{ha} = 0.9$ |
| Pump wear | $\omega_{n,pw} = 7.27rad/s, \zeta_{pw} = 0.75$ |

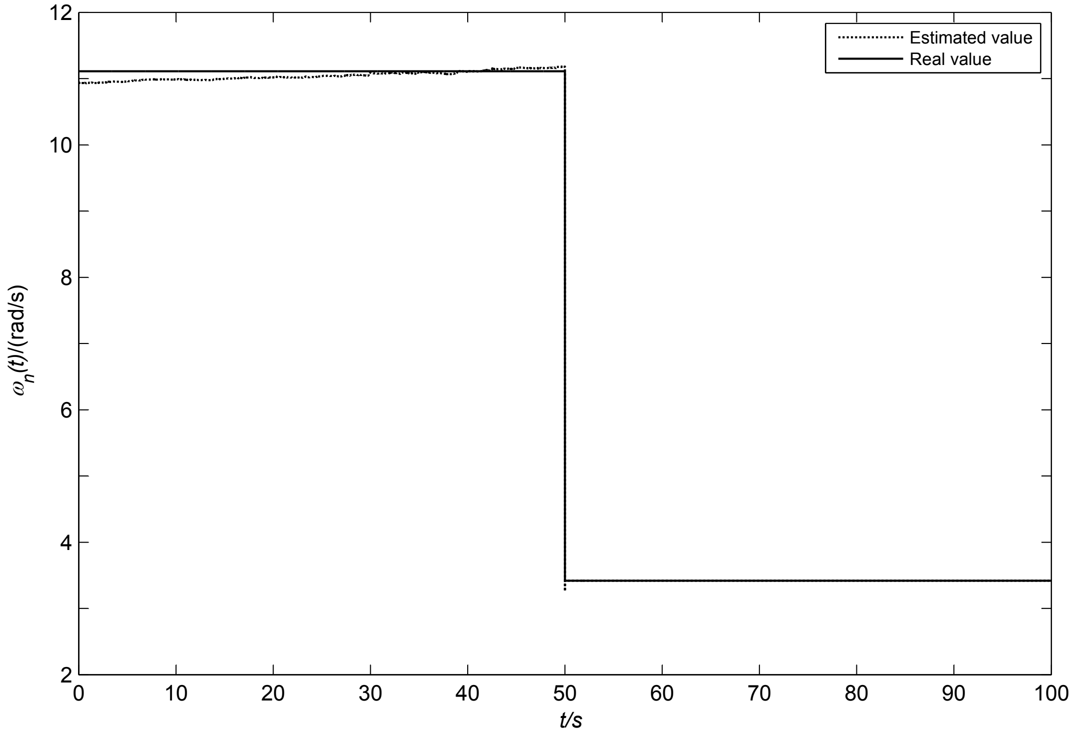


Figure 6: The parameter $\omega_n(t)$ of hydraulic leakage

The parameter estimation results are shown in Fig. 4 and Fig. 8.

When $0s \leq t \leq 50s$, the pitch actuator is in a stable state with no fault, larger forgetting factor $\lambda_{max}$ is chosen for the VFF-RLS algorithm, and the estimation error is smaller. At time $50s$, the fault occurs, and system parameters change correspondingly. The VFF-RLS algorithm will adjust the forgetting factor according to Eq.(27), and smaller $\lambda(t)$ will be chosen to ensure faster convergence speed.

When $50s < t \leq 100s$, the actuator is in fault, $\lambda(t)$ changes to $\lambda_{max}$ automatically to reduce state estimation errors. Thus it is able to automatically adjust according to the forgetting factor to meet the estimation accuracy of the steady-state and the convergence speed of the transient moment. Different fault types can be determined by the magnitude and direction of the parameters' change.

# 5 Conclusion

This paper uses the system identification method for fault diagnosis of the wind turbine hydraulic pitch system actuator , which transmits the problem into a system identification issue. The VFF-RLS algorithm for time-varying systems has a high speed and precision, so parameters of the time-varying system can be estimated. Simulation results validates feasibility and effectiveness of the VFF-RLS based fault diagnosis

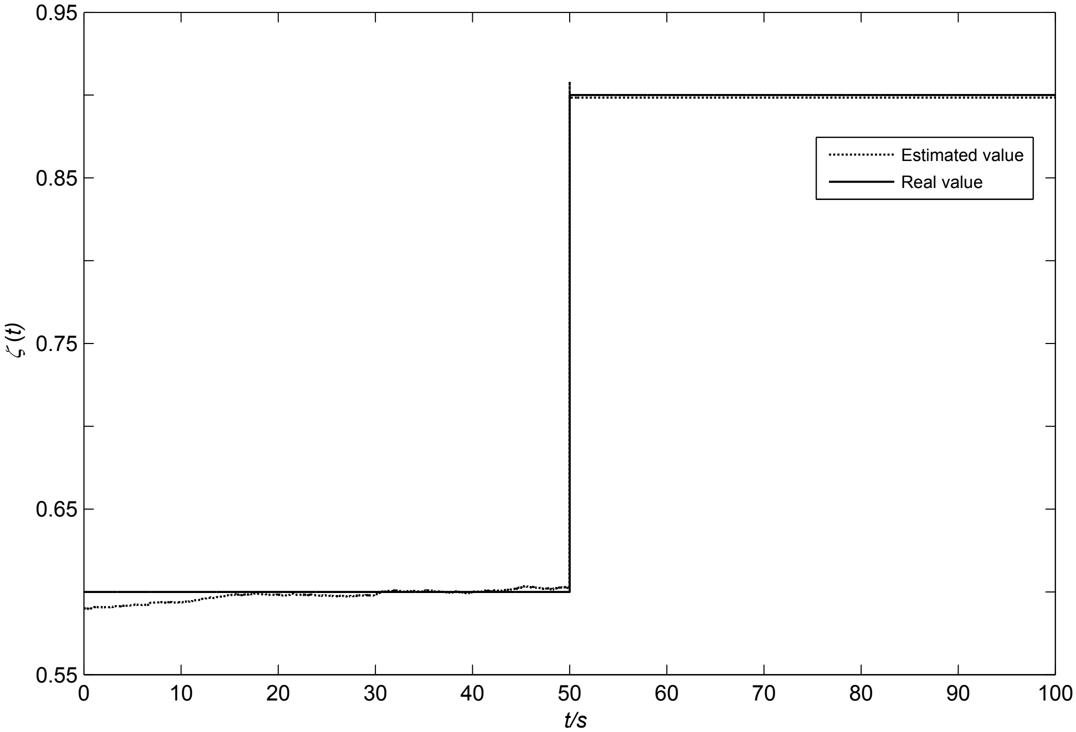


Figure 7: The parameter $\zeta_n(t)$ of hydraulic leakage

method.

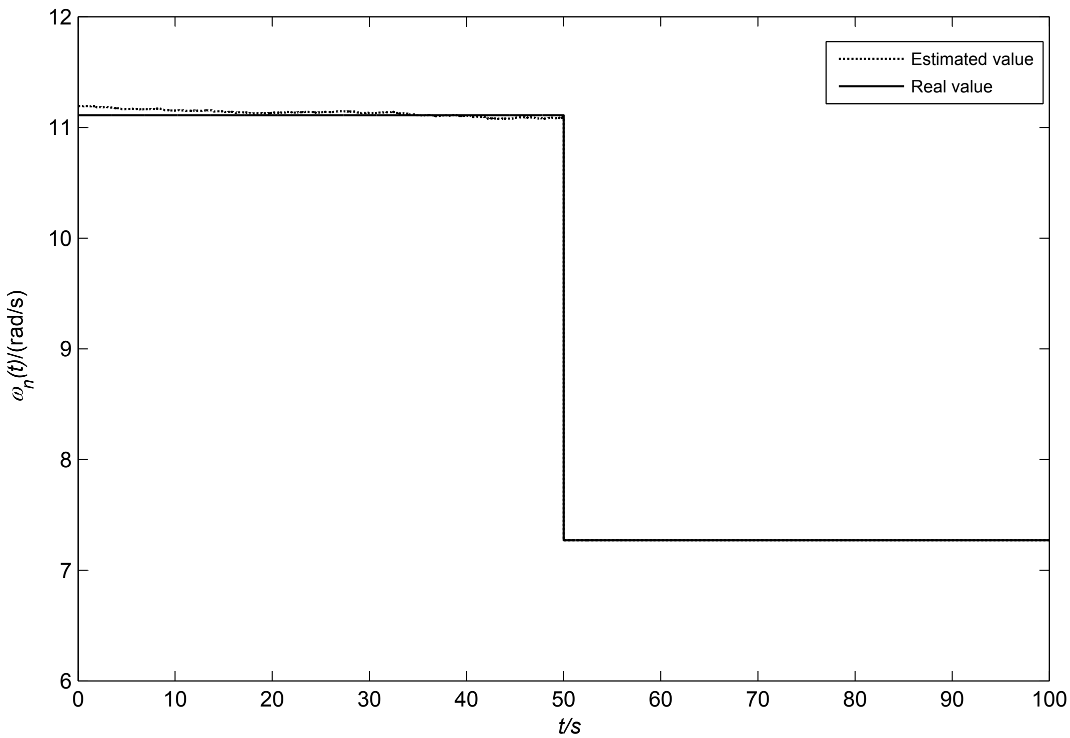


Figure 8: The parameter $\omega_n(t)$ of pump wear

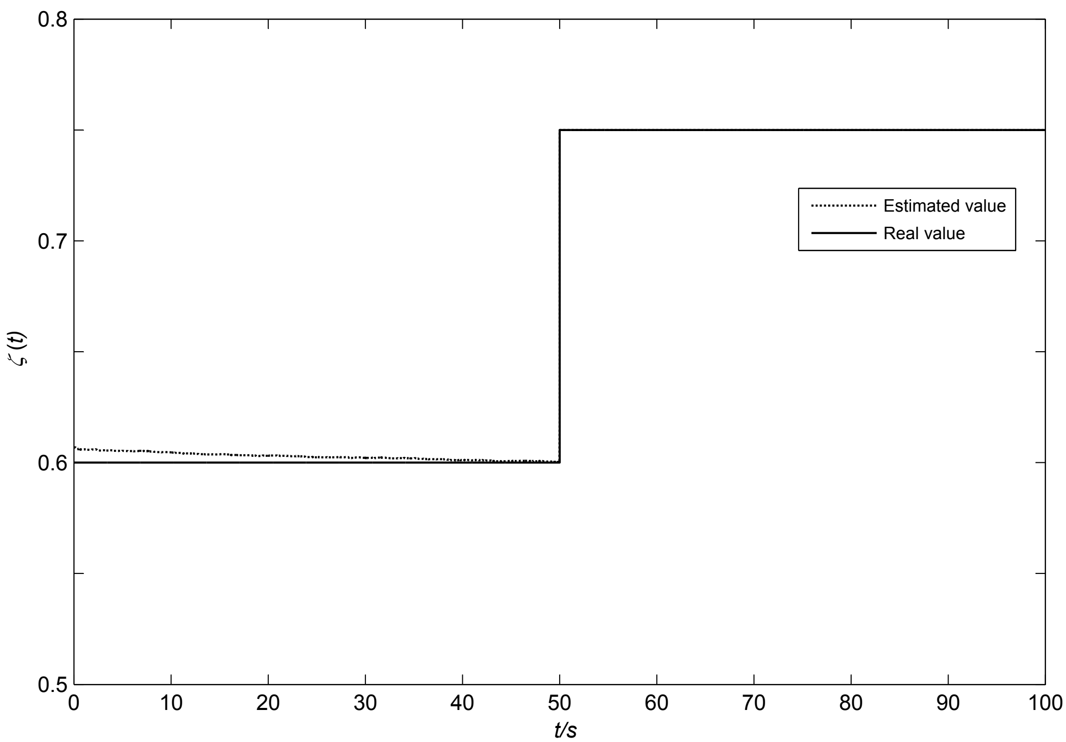


Figure 9: The parameter $\zeta_n(t)$ of pump wear

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