

# Fault Diagnosis of a Nonlinear Dynamic System Based on Sliding Mode

Wenxin Yu<sup>†</sup>, Junnian Wang\* and Dan Jiang\*\*

**Abstract** – Actuator failures and the failures of controlled objects are often considered together. To overcome this limitation, a class of sliding mode observers for the fault diagnosis of nonlinear systems is designed in this paper. Due to the influence of the sliding mode function, the control strategy and the residual change of the observer exhibit certain trends governed by specific relations. Therefore, according to the changes in the control strategy and the observer residuals, the sensor and actuator faults in nonlinear systems can be determined. Finally, the effectiveness of the proposed method is verified based on simulations of a DC motor system.

**Keywords:** Fault diagnosis, Sliding mode, Control strategy.

## 1. Introduction

With developments in computer technology and control theory, mechatronic equipment has been widely applied, and the control system and controlled object have become the main components of this type of equipment. Because of its nonlinearity and strong coupling, the reliability of system operation and the safety of the system can deteriorate. If the system fails and the failure cannot be immediately detected and processed, serious consequences can occur. In many practical fault detection and diagnosis (FDD) analyses of dynamic systems, the physical state variables of systems are partially or fully unavailable for measurements. Specifically, the state variables are not measurable with sensing devices, and the transducers are not available. In such cases, observer-based control schemes should be developed to estimate the state. Therefore, observer design has become a very popular research field over the past decade and is generally considered more challenging than control problems. Reference [1] presents a functional observer-based fault detection method. Fault detection is achieved using a functional observer-based fault indicator that asymptotically converges to a fault indicator that can be derived based on the nominal system. In reference [2], the authors address the dynamic surface control of uncertain nonlinear systems based on composite intelligent learning and disturbance observer methods considering unknown system nonlinearity and time-varying disturbances. Reference [3] presents an observer-based dynamic fuzzy logic scheme for a class of unknown SISO nonlinear dynamic systems with external disturbances.

<sup>†</sup> Corresponding Author: School of Information and Electrical Engineering, Hunan University of Science and Technology, Hunan Pro., Xiangtan, 411201, China; College of Electrical & Information Engineering, Hunan University, Hunan Pro., Changsha, 410082, China. (slowbird@sohu.com)

\* School of Physics and Electronics, Hunan University of Science and Technology, Hunan Pro., Xiangtan, 411201, China.

\*\* School of Information and Electrical Engineering Hunan University of Science and Technology, Hunan Pro., Xiangtan, 411201, China.

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The observer-based fault detection method has been widely used for FDD in dynamic systems [4-12]. The basic concept is to reconstruct the system by measuring the system output and to compare the observer's output with that of the system as a residual to determine whether the system fails. However, this fault detection method only qualitatively determines whether the system fails and cannot provide an extensive understanding of the nature of the fault. However, fault reconstruction can directly provide the associated fault changes and processes, and such methods can be applied to diagnose detailed systems.

The sliding mode observer is a type of nonlinear approach that overcomes the uncertainty or nonlinearity of a system model based on its inherent robustness. Specifically, it maintains the sliding mode motion by introducing an equivalent output control method to obtain the fault information and perform reconstruction. Therefore, in the area of motor control and fault diagnosis, methods such as robot control, fault diagnosis and fault-tolerant control [13-17] have been widely used. When the actuator fails, reference [18] considers the unknown uncertainty bounds and satisfies the matching conditions. A sliding mode observer with a Lipschitz nonlinear system is established through coordinate transformation, and fault detection and reconstruction are performed. Reference [19] uses a high-order sliding mode differentiator to remove the restrictions of relative order conditions and conduct actuator fault diagnosis for a linear system. Halim et al. proposed the design of an adaptive super-helical slip-mode differentiator to reconstruct actuator wobble. An adaptive method was introduced to update the sliding mode gain in real time, which eliminated the noise and the disturbance associated with sliding mode motion [20]. When the sensor fails, both methods proposed in reference [21] can be used to convert the sensor fault to an actuator fault. Then, the sliding mode observer can be designed to obtain the estimated value of the fault and determine the sufficient condition of the observer. Reference [22] first designs the sliding mode observer considering the actuator failure

and then solves the problem of sensor reconfiguration in a similar way through system transformation to further extend the result to a generalized system. For a sensor with a sensor failure in reference [23], the author designs the unknown input observer (UIN) for state estimation. A sensor fault reconstruction method is proposed based on the UIN. In [24], a sliding mode observer-based fault detection and isolation method is developed for induction generator (IG)-based variable-speed grid-connected wind turbines.

In many studies, the actuators and controlled objects are considered together, and the fault of the controlled object element is not directly or indirectly diagnosed from the nonlinear mathematical model of the system, which is not conducive to failure decision making and processing. In this paper, we propose a sliding mode observer according to the control strategy and the variation of observer residuals. Then, the faults of sensors and actuators in nonlinear systems are evaluated. The paper is organized as follows. In Section 1, some proposed methods are summarized and discussed. In Section 2, the proposed sliding mode control strategy and design observer are explained in detail. The effectiveness of the proposed method is tested based on a simulation of a DC motor system in Section 3. Finally, the conclusions are given in Section 4.

## 2. System Assumptions and Observer Structure

### 2.1 Description of the problem

When sensor and actuator failures occur, the mathematical model of the nonlinear system can be expressed as follows:

$$\begin{cases} \dot{x} = Ax(t) + Bu(t) + Mf_a + HF(t, x, u) + Q\xi(t, x, u) \\ y = Cx(t) + Sf_s \end{cases} \quad (2.1)$$

where  $x(t) \in R^n$ ,  $y \in R^p$ , and  $u(t) \in R^m$  are the state vector, measurement output and control input, respectively;  $f_a$  is the actuator failure;  $f_s$  is the sensor failure;  $F(t, x, u)$  is the nonlinear system term; and  $\xi(t, x, u)$  is the unknown input, such as the system disturbance or modeling uncertainty.

$$\begin{aligned} A \in R^{n \times n}, B \in R^{n \times m}, C \in R^{p \times n}, M \in R^{n \times q} \\ H \in R^{n \times q}, Q \in R^{n \times q}, S \in R^{p \times n} \quad (n > p \geq q) \end{aligned}$$

To facilitate the analysis, the following assumptions are made in this paper.

(1) If the nonlinear function  $H(t, x, u)$  satisfies the Lipschitz condition, then

$$\|F(t, x, u) - F(t, \tilde{x}, u)\| \leq \gamma \|x - \tilde{x}\|, (\gamma > 0).$$

(2) Assume that the matrices  $M$  and  $S$  are full rank.

(3) Assume  $f_a, f_s$  and  $\xi(t, x, u)$  are unknown but bounded; then,  $\|f_a\| \leq \alpha(t, u)$ ,  $\|f_s\| \leq \eta(t, u)$  and  $\|\xi(t, x, u)\| \leq \beta(t, u)$ .

### 2.2 Fault observer design

According to (2.1), estimate  $x(t)$ ; then, the fault observer is as follows.

$$\begin{cases} \dot{\tilde{x}} = A\tilde{x}(t) + Bu(t) + HF(t, \tilde{x}, u) - Le_y(t) + Qv \\ \tilde{y}(t) = C\tilde{x}(t) \end{cases} \quad (2.2)$$

To design the sliding mode observer, the following sliding mode function is applied.

$$s = Ee = WCe = W(C\tilde{x} - y) \quad (2.3)$$

For the sliding mode observers of nonlinear systems, this paper proposes the following sliding mode strategy.

$$v = \begin{cases} 0 & \text{if } \|s^T EB\| = 0 \\ -\frac{(s^T EB)}{\|s^T EB\|^2} (\rho \|s\| \|EB\| + \sin s) & \text{else} \end{cases} \quad (2.4)$$

In Eq. (2.4),  $\rho$  is a bounded function, and  $\rho = r \|u(t)\| + \|\xi(t, x, u)\|$ , where  $r$  is a constant.

$e(t) = \tilde{x}(t) - x(t)$  is the state deviation, and  $e_y = \tilde{y}(t) - y(t)$  is the residual of the observer in this paper.

Block diagram of sliding mode observer is shown in Fig. 1.

**Assumption 1.** Define the scalars  $\mu_0$  and  $\mu_1$  so that

$$u_0 = -\lambda_{\max}(PA_0 + A_0^T P), u_1 = \|PQ\|.$$

According to the above formula, we can obtain the

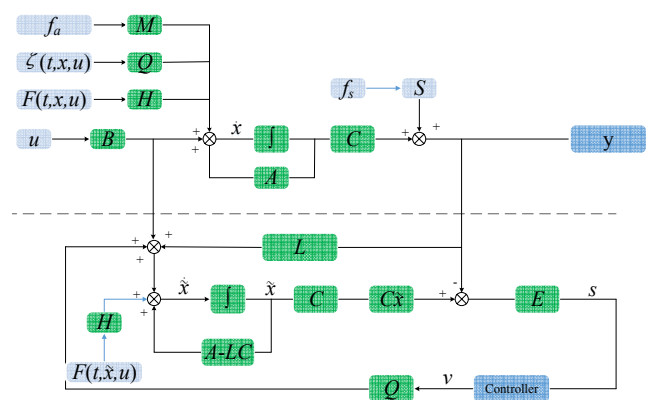


Fig. 1. Block diagram of sliding mode observer

following equation:

$$\begin{aligned} \dot{e}(t) = & A_0 e(t) + Q(v - \xi(t)) - Mf_a \\ & - H[F(x, u, t) - F(\tilde{x}, u, t)] - Sf_s \end{aligned} \quad (2.5)$$

where  $A_0 = A - LC$ .

Next, we demonstrate system stability.

**Theorem 1:** For the sliding mode observer of a nonlinear fault system (2.1), the sliding mode function is given by (2.3), and the control strategy is given by (2.4).

$$\text{If } \alpha\lambda_{\max}(M) + \eta\lambda_{\max}(S) + (\beta - \rho)\lambda_{\max}(G_n) \leq 0,$$

then the observer is asymptotically stable.

**Proof:** Define the Lyapunov function  $V = e^T P e$ , then

$$\begin{aligned} \dot{V} & \leq e^T (PA_0 + A_0^T P)e + 2e^T PQ(v - \xi(t)) - 2e^T PMf_a - 2e^T PSf_s \\ & \leq -\|e\|^2 \frac{u_0}{\lambda_{\max}} + 2e^T PQ \left( -\frac{(s^T MB)}{\|s^T MB\|^2} (\rho\|s\|\|MB\| + \sin s) \right) \\ & \quad - (2e^T PQ\xi(t) + 2e^T PMf_a + 2e^T PSf_s) \\ & \leq -\|e\|^2 \frac{u_0}{\lambda_{\max}} + 2\|e^T\| \lambda_{\max}(P) Q \left( -\frac{(s^T MB)}{\|s^T MB\|^2} (\rho\|s\|\|MB\|) \right) \\ & \quad - 2\|e^T\| \lambda_{\max}(P) (Q\xi(t) + Mf_a + Sf_s) \\ & \leq -\|e\|^2 \frac{u_0}{\lambda_{\max}} + 2\|e^T\| \lambda_{\max}(P) \rho Q \\ & \quad - 2\|e^T\| \lambda_{\max}(P) (Q\xi(t) + Mf_a + Sf_s) \\ & \leq -\|e\|^2 \frac{u_0}{\lambda_{\max}} + 2\|e^T\| \lambda_{\max}(P) \\ & \quad \times (Mf_a + Sf_s + \xi(t)Q - \rho G_n) \\ & \leq -\|e\|^2 \frac{u_0}{\lambda_{\max}} + 2\|e^T\| \lambda_{\max}(P) \\ & \quad \times (\alpha\lambda_{\max}(M) + \eta\lambda_{\max}(S) + (\beta - \rho)\lambda_{\max}(G_n)) \end{aligned}$$

when  $\alpha\lambda_{\max}(M) + \eta\lambda_{\max}(S) + (\beta - \rho)\lambda_{\max}(G_n) \leq 0$ .

Therefore, we can obtain

$$\dot{V} \leq 0.$$

It is obvious that the observer becomes progressively stable.

### 2.3 Determination of the matrix parameter $E$

If we assume that  $e = [e_1 \ e_2]^T$ , the deviation system in (2.5) can be rewritten in the following block matrix form:

$$\dot{e}_1(t) = A_{011}e_1(t) + A_{012}e_2(t) \quad (2.6)$$

$$\dot{e}_2(t) = A_{021}e_1(t) + A_{022}e_2(t) + Q_2(v - \xi(t)) - M_2f_a - S_2f_s \quad (2.7)$$

where

$$\begin{aligned} A_0 & = [A_{011}, A_{012}; A_{021}, A_{022}], \quad A_{011} \in R^{(n-q) \times (n-q)} \\ A_{012} & \in R^{(n-q) \times q}, \quad A_{021} \in R^{q \times (n-q)}, \quad A_{022} \in R^{q \times q}, \\ Q & = [0; Q_2], \quad Q_2 \in R^{q \times q}, \quad M = [0; M_2], \\ M_2 & \in R^{q \times q}, \quad S = [0; S_2], \quad \text{and } S_2 \in R^{q \times q}. \end{aligned}$$

Therefore, the sliding mode system can be expressed as follows:

$$s = E_1 e_1 + E_2 e_2,$$

where  $E = [E_1 \ E_2]$ ,  $E_1 \in R^{q \times (n-q)}$ , and  $E_2 \in R^{q \times q}$ .

When the deviation system (2.5) reaches  $s$ , the dynamic performance of the deviation system will be determined by the linear sliding mode (2.3).

$$s = E_1 e_1 + E_2 e_2 = 0 \quad (2.8)$$

Then,  $e_2 = -E_2^{-1} E_1 e_1$ .

After the above equation is substituted into the deviation system (2.6) at the current time, the system equation after the sliding mode reduction is as follows.

$$\dot{e}_1(t) = (A_{011} - A_{012} E_2^{-1} E_1) e_1(t) \quad (2.9)$$

When  $(A_{011} - A_{012} E_2^{-1} E_1)$  is a Hurwitz matrix, the system of asymptotes converges to the equilibrium point  $e = 0$  after it reaches the sliding mode  $s = 0$ . Thus, the designed sliding mode parameter matrix  $M$  can be obtained.

### 2.4 Fault diagnosis method

Assuming that more than two types of faults do not occur simultaneously in a nonlinear system, the proposed residual generation of the sliding mode observer and fault diagnosis methods are as follows.

(1) If the residual  $e_y$  and control strategies  $v$  are close to zero, the system is not in failure mode.

(2) If the residual  $e_y$  jumps from a zero value at the moment of failure, the control strategy  $v$  also changes a small amount after the delay, and for  $v > 0$ , the jump of this control strategy will always be regular with the fault, but the amplitude change is not large. Then, the nonlinear system sensor is in failure mode, i.e.,  $f_s \neq 0$ .

(3) If the residual  $e_y$  jumps from zero at the moment of failure and the same control strategy  $v$  also exhibits a small delay and jumps (and  $v < 0$ ), then the nonlinear system has an actuator fault, i.e.,  $f_a \neq 0$ ; however, unlike (2), the magnitude of the change varies greatly.

### 3. Examples and Simulation Analysis

Consider the nonlinear DC motor system [25-26] with the following state-space equation:

$$\begin{cases} \begin{bmatrix} \dot{x}_1(t) \\ \dot{x}_2(t) \end{bmatrix} = \begin{bmatrix} -0.4751 & -0.0396 \\ 113.9706 & -0.00952 \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} f_a \\ + \begin{bmatrix} 0 \\ 1 \end{bmatrix} \xi(t) + \begin{bmatrix} 0.1277 \\ 0 \end{bmatrix} u(t) + \begin{bmatrix} 0.0075 \sin x_2(t) \\ 0 \end{bmatrix} \\ \begin{bmatrix} y_1(t) \\ y_2(t) \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} f_s \end{cases}$$

where the state components  $x_1$  and  $x_2$  are the armature current (A) and motor angular velocity (rad/s), respectively, and  $u$  is the input armature voltage (V). The interference is set to  $\xi(t) = 0.003 \sin 5t$  in the DC motor system. The following actuator and sensor faults occur.

$$f_a(t) = \begin{cases} 0, & 0 \leq t < 25 \\ 2 \sin(2t) \cos t + 5, & 25 \leq t \leq 50 \end{cases} \quad (3.1)$$

$$f_s(t) = \begin{cases} 0, & 0 \leq t < 25 \\ 5(1 - e^{-t}) + \sin \pi t, & 25 \leq t \leq 50 \end{cases} \quad (3.2)$$

In this paper, the observer pole configuration is set in the range of  $(-3 + 0.88i; -3 - 0.88i)$  when calculating the gain matrix  $L$  to reduce the complexity of the nonlinear equation. Additionally,  $f_a, \xi(t)$  and  $\sin x_2(t)$  are set to 0 to easily obtain the gain matrix  $L$  by applying the linear pole configuration.

Therefore,  $L = \begin{bmatrix} 2.5249 & -0.9196 \\ 114.8506 & 2.9905 \end{bmatrix}$ .

Based on equation (2.4), we choose  $r = 0.0486$  and obtain  $\rho = 14.59571548$ . According to the matrix parameter determination,  $-M_2^{-1}M_1 = \frac{3.41}{1}$  is obtained after

a simple calculation, and the result is the minimum value of  $-M_2^{-1}M_1$ . In the process of obtaining the gain matrix  $L$ , we linearize the nonlinear system. To compensate for changes in the system, and for convenience, we set  $-M_2^{-1}M_1 = \frac{4}{1}$  here. After repeated tests,  $E = [4, 1]$  is shown

to meet the requirements of the observer. Therefore, the sliding surface is designed based on the following formula.

$$s = 4e_1 + e_2 \quad (3.3)$$

#### Case 1 - No fault condition

Fig. 2 illustrates that the  $v$ -curve remains at zero after a brief change because the deviation in the system quickly

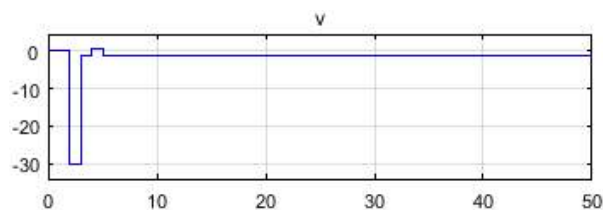


Fig. 2. v-curve

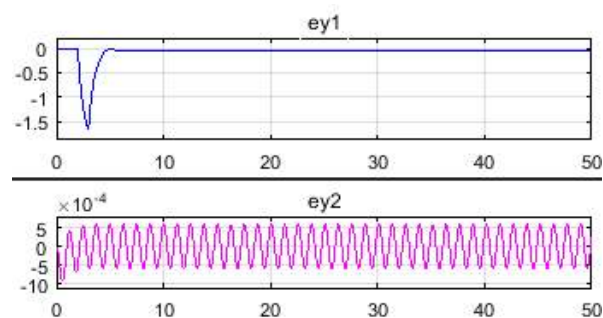


Fig. 3. Residual curve

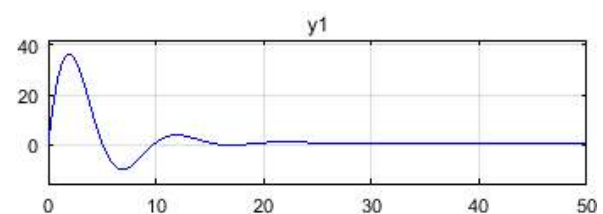


Fig. 4.  $y_1$  output curve

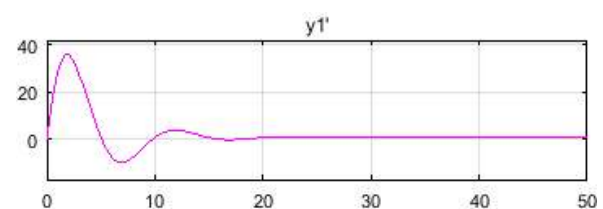


Fig. 5.  $y_1$  estimated output curve

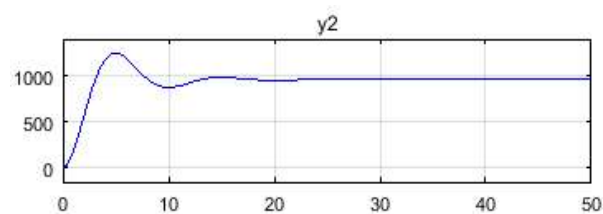


Fig. 6.  $y_2$  output curve

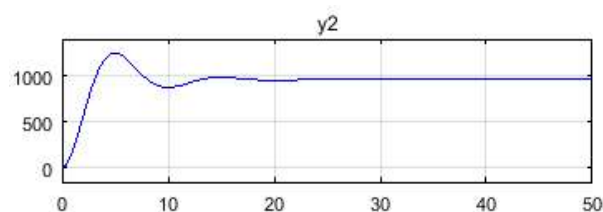
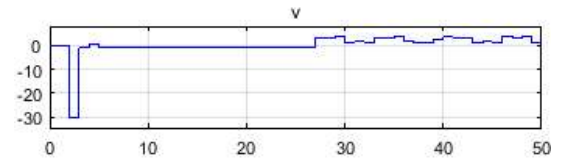


Fig. 7.  $y_2$  estimated output curve

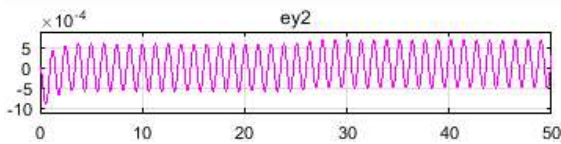
reaches the sliding surface  $s = 0$ . As shown in Fig. 3, the residual  $e_y$  is close to 0. The estimated outputs  $y_1'$  and  $y_2'$  accurately reflect outputs  $y_1$  and  $y_2$ , respectively, in Figs. 4-7.

**Case 2 - Actuator failure condition**

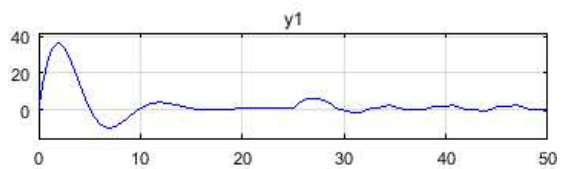
When actuator failure occurs, Figs. 8-13 show that the



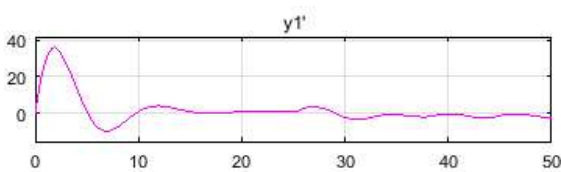
**Fig. 8.** v-curve



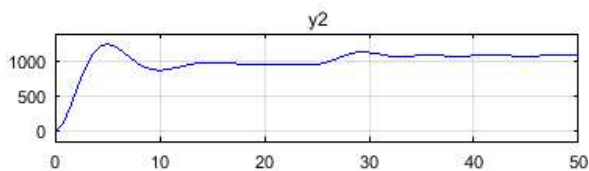
**Fig. 9.** Residual curve



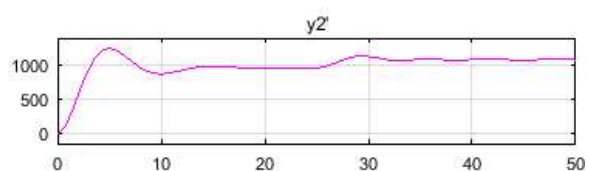
**Fig. 10.**  $y_1$ -outputs curve



**Fig. 11.**  $y_1$ -estimated outputs curve



**Fig. 12.**  $y_2$ -outputs curve

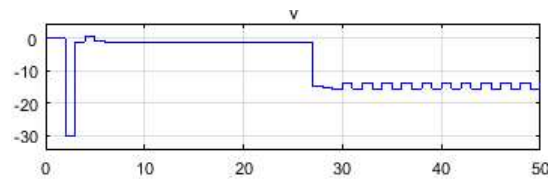


**Fig. 13.**  $y_2$ -estimated outputs curve

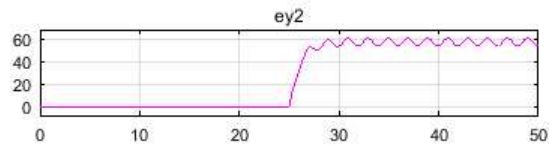
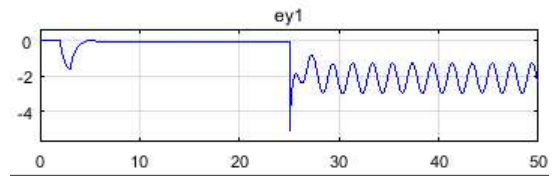
condition of the sliding mode plane  $s = 0$  is damaged at the moment of failure; therefore,  $s \neq 0$  and  $v > 0$  after a very short delay. Moreover,  $e_y$  is no longer 0, and a slight jump occurs. However, the estimated outputs  $y_1'$  and  $y_2'$  are still able to accurately reflect outputs  $y_1$  and  $y_2$ , respectively.

**Case 3 - Sensor failure condition**

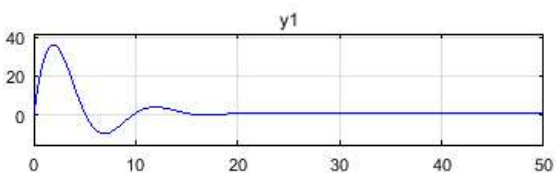
Figs. 14-19 show that in the event of a sensor failure, similar to the case of actuator failure, the condition of the sliding plane  $s = 0$  is destroyed. Additionally, after a very



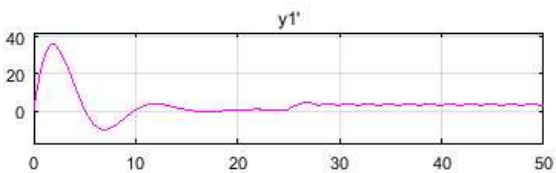
**Fig. 14.** v-curve



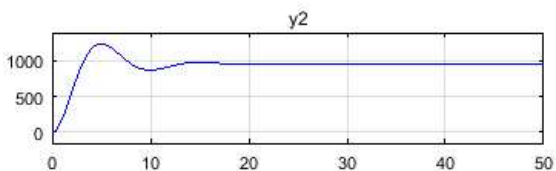
**Fig. 15.** Residual-curve



**Fig. 16.**  $y_1$ -outputs curve



**Fig. 17.**  $y_1$ -estimated outputs curve



**Fig. 18.**  $y_2$ -output curve



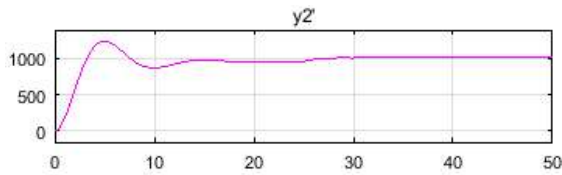


Fig. 19.  $y_2$ -estimated output curve

short delay,  $v < 0$ , and  $e_y$  is no longer 0. Unlike actuator faults, sensor faults will result in large residuals. Additionally, the estimated outputs  $y_1'$  and  $y_2'$  accurately reflect the outputs  $y_1$  and  $y_2$ , respectively.

#### 4. Conclusion

In this paper, a sliding mode observer is designed for the fault diagnosis of nonlinear systems. According to the control strategy and the variation in observer residuals, sensor and actuator faults in nonlinear systems are evaluated. Finally, the fault diagnosis observer designed in this paper is applied for fault reconstruction in a DC motor system. The simulation results illustrate the feasibility and effectiveness of the proposed method.

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**JunNian Wang** received the B.Sc. degree in Physics from Lanzhou University, Lanzhou, China, in 1991, the M.S. degree in Radio Physics from Lanzhou University, Lanzhou, in 2000, and Ph.D. degree in Control Theory and Control Engineering from Central South University, Changsha, in 2006.

He joined the Hunan University of Science and Technology, where he currently is a professor in the School of Physics and Electronics. His interests include complex systems, intelligent control, and intelligent fault diagnosis.



**Dan Jiang** was born in Hunan, on October 7, 1994. She received the B.E. degree in electrical engineering from Hunan University of Science and Technology, Xiangtan, Hunan, in 2016. She is currently working toward the M.S. degree at Hunan University of Science and Technology, Xiangtan, Hunan.

Her research interest include intelligent algorithm and faults diagnostic analysis.



**WenXin Yu** received the B.Sc. degree in applied mathematics from Hebei Normal University, Shijiazhuang, China, in 2005, the M.S. degree in wavelet analysis from Changsha University of Science & Technology, Changsha, in 2008, and Ph.D. degree in electrical engineering from Hunan University,

Changsha, in 2015. He joined the Hunan University of Science and Technology, where he currently is a lecturer in the School of Information and Electrical Engineering. His interests include the research of intelligent control, fault diagnosis, signal processing, wavelet analysis and its application.