



FAULT DIAGNOSIS AND PERFORMANCE ASSESSMENT FOR A ROTARY ACTUATOR BASED ON NEURAL NETWORK OBSERVER

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Key words: rotary actuator, fault observer, fault detection, fault isolation, performance assessment, neural network.

ABSTRACT

Substantial damage may occur when a rotary actuator fails during operation. Therefore, effective fault diagnosis of a rotary actuator is crucial to ensuring the safety of the device. However, only a few studies on fault detection, fault isolation, and performance assessment have focused on rotary actuators. In this study, fault detection and fault isolation processes were implemented by designing two observers based on a neural network, and a method that assesses the performance of the rotary actuator is proposed. First, two observers are established according to the structure of the rotary actuator. Data in their normal state are used to train the neural networks. Second, a radial basis function (RBF) neural network is employed to estimate the expected output of the system to generate residuals, and self-adaptive thresholds are obtained through another RBF neural network in each observer. The information on the observers is applied for fault isolation. Third, the residual is input into the self-organizing mapping neural network trained by the residual values in their normal state to normalize the performance of the rotary actuator into confidence values between 0 and 1. Finally, the detection and assessment of two typical faults in a rotary actuator were simulated. The results demonstrate that the proposed method is able to assess the performance of rotary actuator and detect faults suitably.

I. INTRODUCTION

A rotary actuator for which hydraulic oil is the source of power has a direct rotary structure [8]. Hydraulic rotary actuator with the advantages of a large torque/quality ratio,

simple compact structure, and fast dynamic response, has been widely implemented in ships, tanks, and, specifically, the wing flaps and door actuating devices of aircraft. An abnormality in the structure of a rotary actuator may result in a disaster if an equipment shutdown occurs during operation. Therefore, ensuring the reliable operation of the rotary actuator is crucial.

Fault detection, isolation, and performance assessment based on data driving have attracted increasing attention. Zhang *et al.* [11] established failure models by analyzing the fault characteristics of induction motor stator winding and rotor winding and by designing a robust observer using the state-space mathematical model of an induction motor d-q coordinate system. Song *et al.* [6] proposed a method for diagnosing faults in flight control systems by using a radial basis function (RBF) neural network observer, which resolved the fault diagnosis difficulties of nonlinear system by analytical methods. Lu [5] proposed an approach for assessing the conditions of bearings according to chaotic characteristics. Jayakumar and Das [3] proposed a method for fault detection, isolation, and reconfiguration for flight control systems based on a single Luenberger observer. Liu *et al.* [4] proposed a method for isolating and reconfiguring faults in flight control systems by establishing a set of robust adaptive observers.

Data-driven methods have been widely used in numerous fields. However, few studies of fault detection and performance assessment have focused on rotary actuators. Furthermore, interference has also been ignored in fault detection and assessment. To solve these problems, a fault detection and performance assessment method based on an RBF neural network that focuses on rotary actuators was proposed in this paper.

II. STRUCTURE OF A ROTARY ACTUATOR

A rotary actuator consists of a control module, a servo valve, a hydraulic motor, a transmission mechanism, and an execution mechanism. As shown in Fig. 1, two angular displacement feedback loops in the control loop help the execution mechanism reach the correct angle. The system feeds the angle signal back to the control module when the execution

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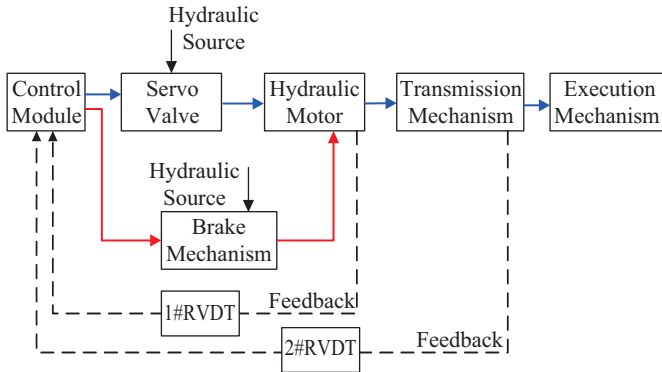


Fig. 1. Structure of rotary actuator.

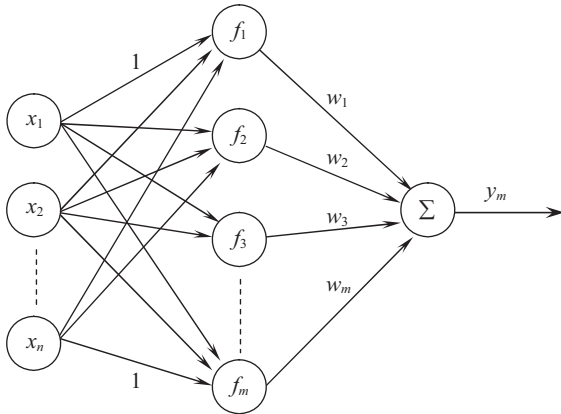


Fig. 2. RBF neural network.

mechanism reaches the expected angle; the control instruction is then changed to the brake mechanism (red line in Fig. 1) and brakes the hydraulic motor to ensure that the motor maintains the execution mechanism at an appropriate angle.

Obtaining the parameter values of the servo valve and hydraulic motor is difficult in practice. However, the data that can be obtained are the control signals and the feedback of the transmission mechanism during simulation.

III. SELF-ADAPTIVE FAULT DETECTION FOR ROTARY ACTUATOR

1. Radial Basis Function Neural Network

A neural network with the capability to approximate any nonlinear function can be used to provide a general recognition mode for nonlinear systems. Establishing a recognition format based on mathematic models of systems is unnecessary. Therefore, as the recognition model of a system, a neural network can be used to realize condition estimates.

An RBF neural network is a type of feed forward network comprising an input layer, a hidden layer, and an output layer, as shown in Fig. 2. $X = [x_1, x_2, \dots, x_n]$ is the input, $F = [f_1, f_2, \dots, f_m]$ is the function of the hidden layer, $W = [w_1, w_2, \dots, w_m]$ is the weight from the hidden layer to the output layer, and

y_m is the output. The input layer consists of several source nodes, such as sensor units that connect to the outside environment. This architecture has only one hidden layer that uses nonlinear transformation from input space to hidden space, namely [1].

Different from a general BP neural network, RBF neural networks have fewer neurons, a higher rate of convergence, a shorter training time, and a higher predictive accuracy. Therefore, we built a system model by using an RBF neural network in this study.

2. Observer Design

Residuals represent the difference between the actual and expected output signals of a rotary actuator; the residuals are defined in [7]:

$$\gamma_i = u_i - \hat{u}_i \tag{1}$$

where γ_i is the value of a residual, u_i is the actual output of a rotary actuator, and \hat{u}_i is the expected output.

When a rotary actuator is abnormal, the deviation between the actual output and the expected output and, thus, the values of the residuals, increases. When a rotary actuator malfunctions, the residuals reach a value that cannot be afforded. A fault is detected when the residuals exceed a specific threshold; it can be used to detect whether a system has a fault by comparing data with a given threshold.

The output of a system does not depend only on the input signal in an analysis of the operating principle of rotary actuators. Random disturbance, the condition of the system, and variable operating conditions can also substantially affect residual generation. A high false alarm rate or low fault detection rate (FDR) may occur if changes caused by nonfault factors are ignored. To solve these problems, in this study, a self-adaptive threshold was introduced into detection to eliminate the effects of nonfault factors on the values of the residuals.

Each observer contains two neural networks. One RBF neural network is employed to estimate the expected output of the system to generate the residuals, and the other neural network is used to obtain the self-adaptive thresholds.

3. Residual and Threshold Generation

A rotary actuator is a closed-loop control system in which the values of the parameters of the inner parts are difficult to obtain; however, input and output signals can be obtained. In the proposed detection method, the control signals, the previous-moment output signals in their normal state and time are used as input ($X = [c_i(k); u_i(k-1); t_i] \ i = 1, 2, \dots, n$) for the RBF neural network, and the output signals are used as target values ($y = [u_i(k)] \ i = 1, 2, \dots, n$) for training the RBF neural network. After training, the observer based on the RBF is created. When test data are inputted, the observer estimates the values of normal output signals, and the residuals of the test data are obtained by calculating the difference between the actual output signal and the expected output signal.

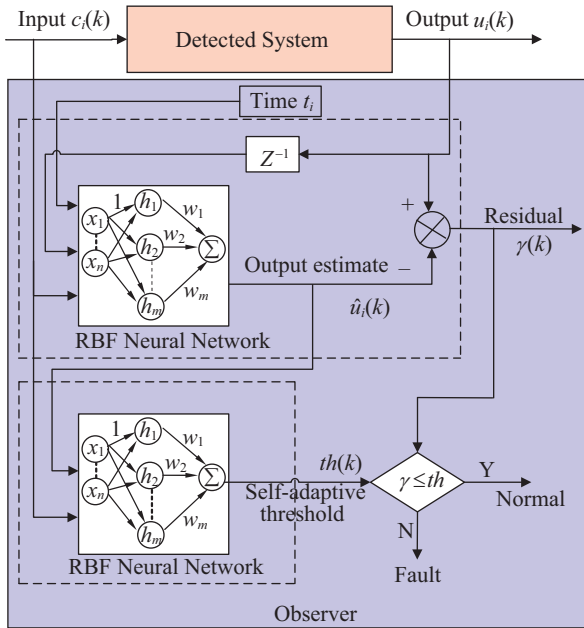


Fig. 3. Observer design.

The self-adaptive threshold, which is defined as a threshold change in the input order and system condition, can be obtained through the trained RBF neural network. During training of the RBF neural network, the control order and output estimate in a normal condition are the inputs for the network, and the expected threshold is the target value. The expected threshold is defined as follows:

$$\hat{th} = \gamma_i + b \tag{2}$$

where \hat{th} is the expected threshold, γ_i is the residual, and b is the correction coefficient.

After the training of the RBF neural network, the self-adaptive threshold is established. The observer, based on two RBF neural networks, is created for fault detection. First, the test data are input into one of the RBF neural network observers that has been trained to generate the residual. Second, the output estimate and control order are regarded as the inputs of the second network for obtaining the self-adaptive threshold. The residual and self-adaptive threshold are compared to confirm whether the residual is higher than the threshold, indicating that the rotary actuator system has a fault. Fig. 3 shows the entire process of self-adaptive fault detection.

IV. FAULT ISOLATION FOR ROTARY ACTUATOR

1. Fault Isolation

Fault isolation, which is defined as the insulation of a faulty subsystem or component in a system, is crucial for maintaining a rotary actuator. A strategy for isolating faults in a rotary

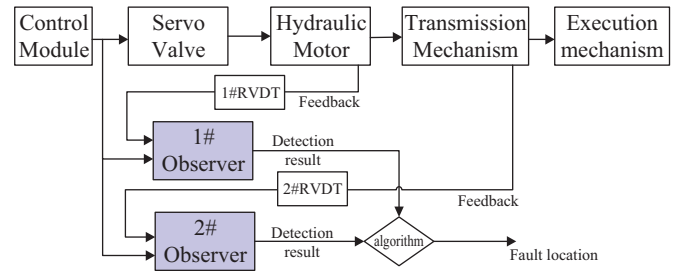


Fig. 4. Strategy of fault isolation.

actuator, based on the information provided by observers, is presented here according to the structural analysis of a rotary actuator.

2. Strategy for Fault Isolation

As shown in Fig. 1, the control loop consists of two loops. Two RVDTs feed the angular displacement back to the control module. The servo valve, hydraulic motor, and 1#RVDT are in the 1# loop. The servo valve, hydraulic motor, transmission mechanism, and 2#RVDT are in the 2# loop.

Therefore, two observers can be built to monitor the two loops. Because various loops consist of various components, the fault localization is confirmed according to the results of fault detection. Fig. 4 shows the fault isolation strategy for a rotary actuator.

If detection results from both observers are normal, the rotary actuator is in a normal condition. When the 1# and 2# observers detect a fault, the fault is in the servo valve or hydraulic motor, respectively. A fault in 1#RVDT can be detected only when the detection result of the 1# observer expresses “fault,” and the detection result of the 2# observer is normal. The fault location can be identified in the transmission mechanism or in 2#RVDT when the result of the 1# observer is normal and that of the 2# observer is not. Table 1 shows the algorithm for fault isolation.

V. PERFORMANCE ASSESSMENT OF ROTARY ACTUATOR

1. Confidence Values and Self-Organizing Map Neural Networks

As an evaluation parameter of the operating condition of a device, confidence values (CVs) can effectively represent the performance assessment results of a rotary actuator.

CVs are generated by normalizing the performance of the rotary actuator to values between 0 and 1. When a device operates normally, CV is close to 1; if the device is going to fail, CV is approaching 0 correspondingly. This method can be used to determine the health condition, subhealth condition, or fault condition of a rotary actuator.

A self-organizing map (SOM) network is a type of competitive artificial neural network that can be used to project multivariate data as well as perform density approximation

Table 1. Isolation results under different detection results.

Detection result	1# Observer	2# Observer	Fault location
1	normal	normal	
2	fault	fault	Servo valve, hydraulic motor
3	fault	normal	1#RVDT
4	normal	fault	2#RVDT, Transmission mechanism

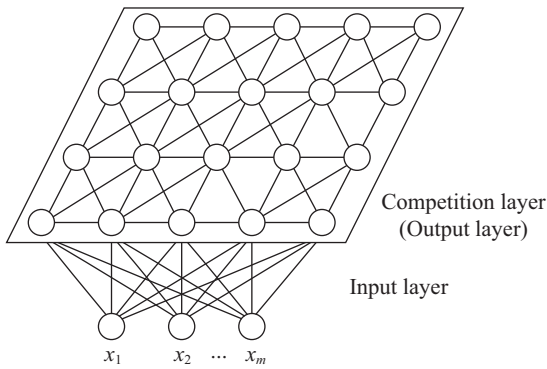


Fig. 5. SOM neural network.

and clustering. A SOM network combines an input layer with a competitive layer of processing neurons, which are typically organized in a two-dimensional grid. The SOM network is an array of $M = m \times n$ processing neurons and maps high-dimensional input vectors onto a two-dimensional surface on which each neuron is represented by a one-dimensional weight vector. Fig. 5 shows the SOM neural network [9].

2. Performance Assessment Based on Residual Analysis

Each neuron of the SOM neural network is represented by a dimensional weight vector. The map neurons are connected to adjacent neurons by a neighborhood relation, which determines the map topology [2]. For example, during training with vector \mathbf{X} , the distances between this vector and all of the SOM weight vectors are computed by using a distance measure. The closest neuron to \mathbf{X} is called the best matching unit (BMU) [10]. The weight vector of the BMU, as well as that of its neighbors, is enhanced by the learning rule written as follows:

$$w_i(t+1) = w_i(t) + \alpha(t) \cdot h_{BMU,i}(t)(x(t) - w_i(t)) \quad (3)$$

where $w_i(t)$ is the weight vector, $\alpha(t)$ is the learning rate for the range $0 < \alpha(t) < 1$, and $h_{BMU,i}(t)$ is the neighborhood function determined by the distance between the BMU and its neighbor. After the training of the SOM neural network by a residual in the normal state, the residual of test data is input

Table 2. Fault mode.

	Fault	Fault mode
1	Reduction in magnetic field strength of servo valve	Flow decrease
2	internal leakage of hydro-motor	Efficiency reduction of driven device
3	Stiffness degradation of transmission shaft	Stiffness degradation
4	Precision abnormal of 2# RVDT	Output abnormal

Table 3. Fault injection.

	Fault	Fault injection
1	Reduction in magnetic field strength of servo valve	$Q' = Q_0 \times 0.7$
2	Internal leakage of hydro-motor	$C_{lm}' = 10e - 12$ $eta-V_m' = eta-V_m \times 0.7$
3	Stiffness degradation of transmission shaft	$\rho' = \rho \times 0.7$
4	Precision abnormal of 2# RVDT	$\alpha' = 0.32$

into the trained SOM neural network. The MQE is then obtained and defined as follows:

$$MQE = \|X_{input} - w_{bmu}\| \quad (4)$$

where X_{input} is the input data vector, and w_{bmu} is the weight vector of the BMU. The value of MQE is normalized to 0 and 1 by using the following function formula:

$$CV = e^{-\sqrt{MQE}/a} \quad (5)$$

where a is a scale parameter that is determined according to the MQE in a normal state and the predetermined CV.

VI. CASE STUDY

1. Fault Injection

A simulation model was used to evaluate the proposed method. Five typical types of faults was injected, namely a reduction in the magnetic field strength of the servo valve, internal leakage of the hydromotor, stiffness degradation of the transmission shaft, and precision abnormality in 2#RVDT, as shown in Table 2. Table 3 shows the method for inputting the faults. Q_0 represents the flow of the servo valve; C_{lm} and $eta-V_m$ represent the leakage coefficient and volume efficiency, respectively; ρ indicates the stiffness of the transmission shaft; and α is the coefficient of the precision of 2#RVDT.

2. Neural Network Training

The control signal and the previous-moment output were input into the neural network.

Figs. 6 and 7 (the red curve represents the self-adaptive threshold and the blue curve is the residual) show that the

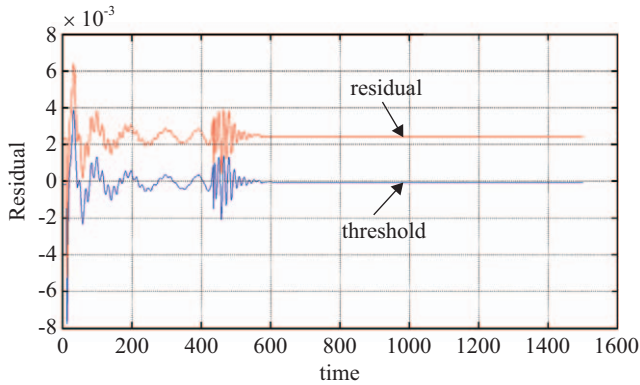


Fig. 6. Residual and threshold in normal state of 1# observer.

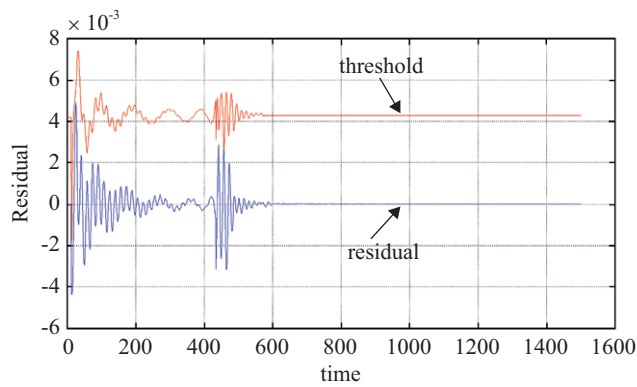


Fig. 7. Residual and threshold in normal state of 2# observer.

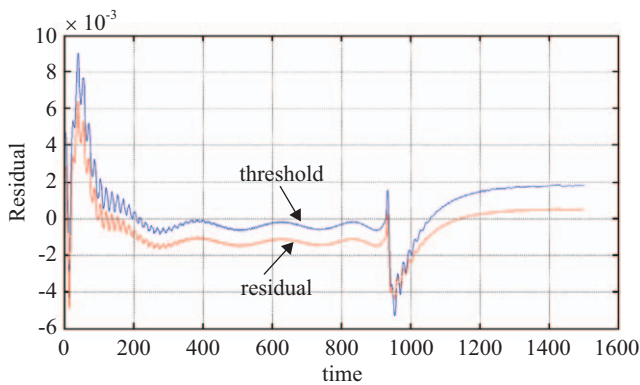


Fig. 8. Reduction in magnetic field strength of servo valve of 1# observer.

threshold was higher than the corresponding residual when the rotary actuator was in a normal state.

3. Reduction in Magnetic Field Strength of Servo Valve

A fault reducing the magnetic field strength of the servo valve was input into the simulation. Figs. 8 and 9 show the detection results of the 1# and 2# observers. A fault was clearly detected by both observers. The faulty component could be located at the servo valve or the hydraulic motor, as shown in Table 1.

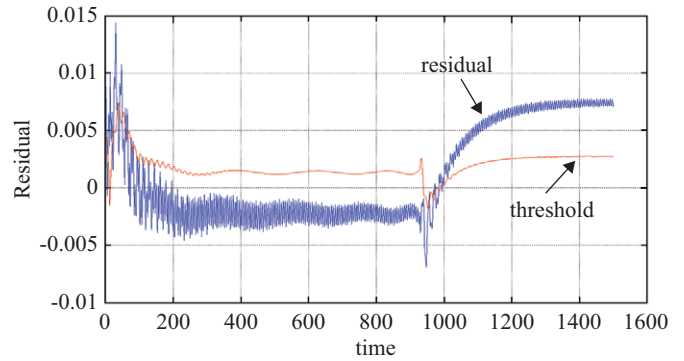


Fig. 9. Reduction in magnetic field strength of servo valve of 2# observer.

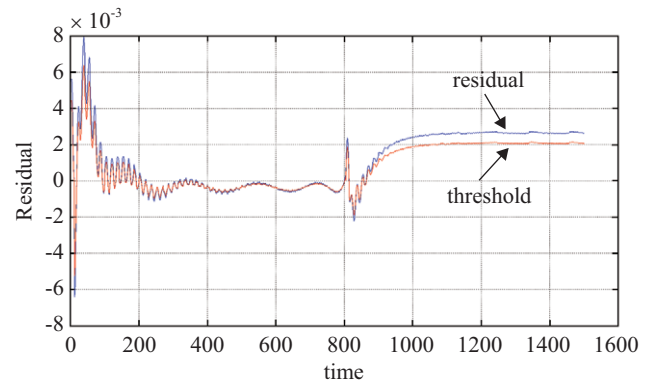


Fig. 10. Internal leakage of hydro-motor of 1# observer.

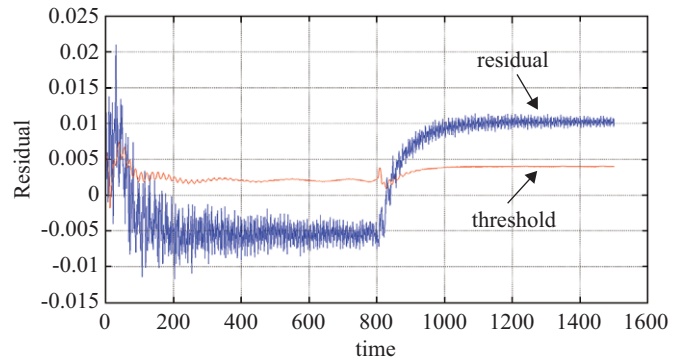


Fig. 11. Internal leakage of hydro-motor of 2# observer.

4. Internal Leakage of Hydromotor

Internal leakage of the hydromotor was input into the simulation. Figs. 10 and 11 show the detection results of the 1# and 2# observers. A fault was clearly detected by both observers. The faulty component could be located at the servo valve or the hydraulic motor, as shown in Table 1.

5. Stiffness Degradation of Transmission Shaft

Stiffness degradation of the transmission shaft was input into the simulation. Figs. 12 and 13 show the detection results of the 1# and 2# observers. The detection result of the 1# observer was normal, and the 2# observer detected the fault,

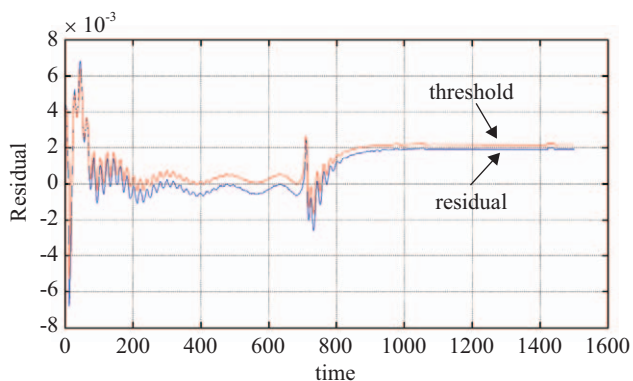


Fig. 12. Stiffness degradation of transmission shaft of 1# observer.

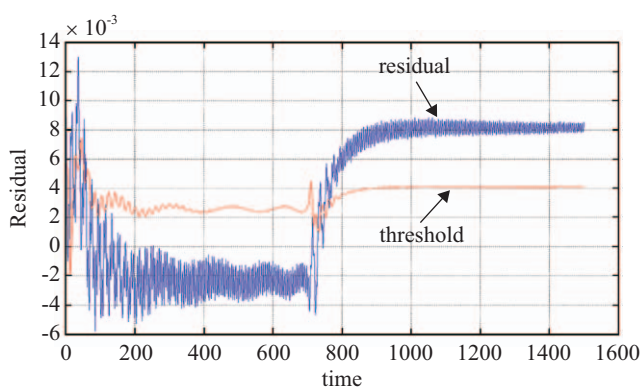


Fig. 13. Stiffness degradation of transmission shaft of 2# observer.

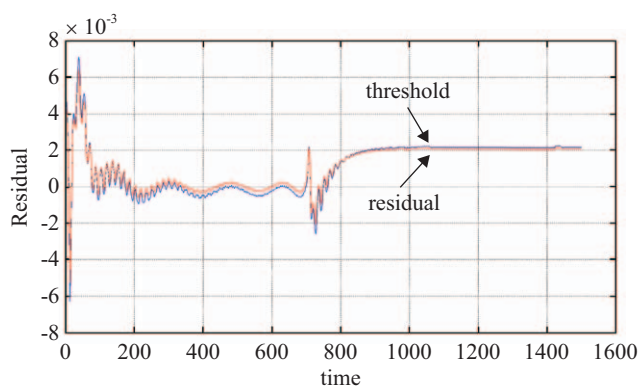


Fig. 14. Precision abnormality of 2# RVDT of 1# observer.

indicating that the faulty component was 2#RVDT or the transmission mechanism, as shown in Table 1.

6. Precision Abnormality in 2#RVDT

Precision abnormality in 2#RVDT was input into the simulation. Figs. 14 and 15 show the detection results of the 1# and 2# observers. Only the 2# observer detected the fault, indicating that the faulty component was 2#RVDT or the transmission mechanism, as shown in Table 1.

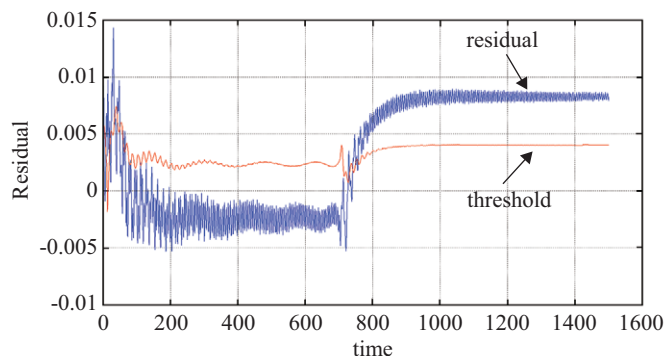


Fig. 15. Precision abnormality of 2# RVDT of 2# observer.

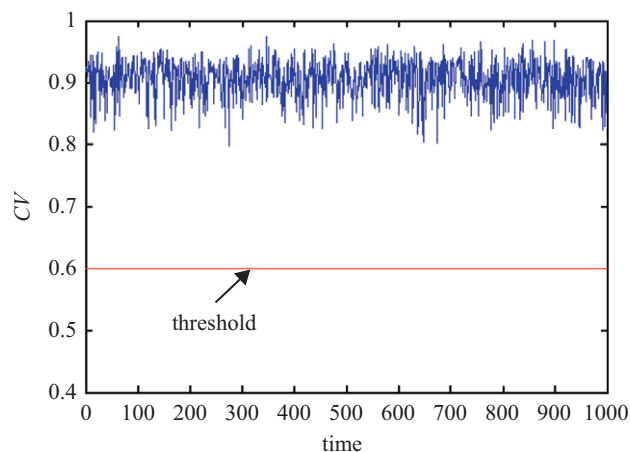


Fig. 16. Performance assessment of normal state.

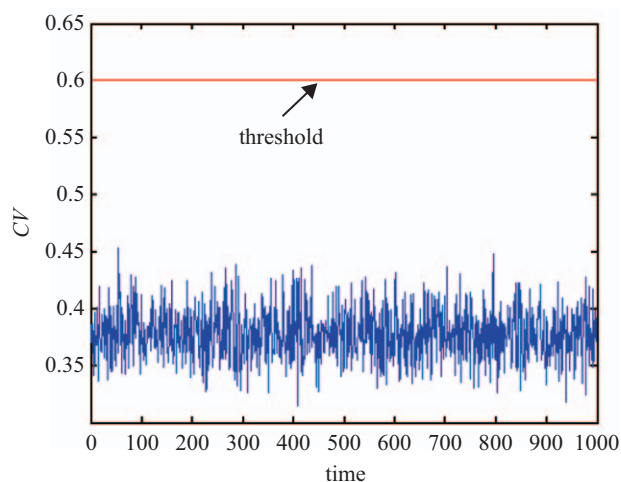


Fig. 17. Performance assessment of reduction in magnetic field strength of servo valve.

7. Results of Performance Assessment

The residual was used in the normal state to train a SOM neural network, and the fault data were input into the trained neural network.

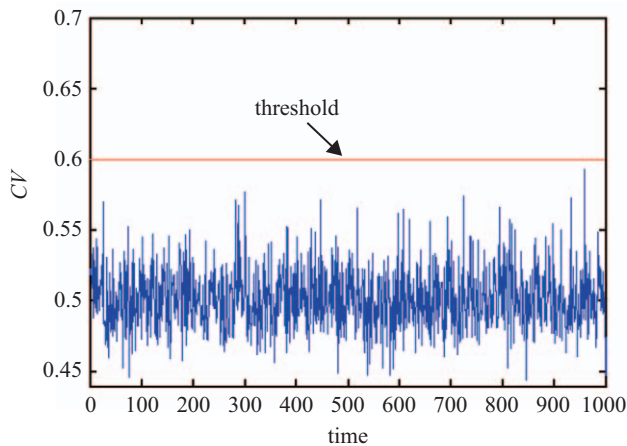


Fig. 18. Performance assessment of stiffness degradation of transmission shaft.

The performance CVs calculated using the proposed method are shown in Figs. 16-18. These values indicate the performance of the rotary actuator and show that the assessment value was lower than 0.6 when a fault occurred.

VII. CONCLUSION

This paper offers a solution for fault detection, isolation, and performance assessment for use in rotary actuators. Two RBF neural networks are used in each observer to generate the residual and a self-adaptive threshold. Two fault observers execute detection and isolation according to the structure of the control loop of the rotary actuator. The residual is input into a SOM neural network, and the performance of the rotary actuator is normalized to CVs between 0 and 1. Several faults were input into a simulation after the fault mode of the rotary actuator was analyzed. The results indicated that the method can accurately detect the faults of the rotary actuator and determine the faulty component. The results of a performance assessment verified the efficiency of the method.

The proposed method could be extended to wider applications. Considering variable load conditions, which are an input of observers, can facilitate suppressing the interference from variable load conditions. Furthermore, new signals can be obtained by adding sensors, such as acceleration sensors, to

build additional observers, which can increase the FDR and fault isolation rate. These aspects are expected to be examined in future study on rotary actuators.

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