Sensor Condition Monitoring Incorporating Fault-tolerant Control

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With the increase in the requirement for control system reliability, fault-tolerant control has become an active research field. For sensor faults in nonlinear systems, based on the idea of active fault-tolerant control, the active fault-tolerant control method with double fault-tolerant controller switching is designed to solve the problem of fault-tolerant control of the system in the case of sensor faults, considering the factor of sudden load changes. Based on fault diagnosis, the method uses diagnostic information and historical data to estimate and compensate the impact of faults on the state estimation of the extended Kalman filter and then uses the compensated state estimation to design a fault-tolerant controller with state feedback that satisfies the stability condition to ensure that the system can operate safely in the case of sensor multiplicative faults. To further improve the dynamic quality. Based on the fault information contained in the deviation between the state estimate of the extended Kalman filter and the one-step prediction estimate, a fault-tolerant control method with a multi-step prediction value instead of the filter valuation constituting the state feedback is proposed to exclude the influence of sensor faults and improve the dynamic performance of the fault-tolerant control. Also, the method can effectively solve the fault-tolerant control problem of additive sensor faults. The simulation results verify the effectiveness of the method.

Keywords: Sensor; Sensor failure; Active fault-tolerant control

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1. Introduction

Modern production lines can be highly automated, but the key is to use a lot of sophisticated sensors [1], which can gather a variety of equipment and process data at the production site, giving the automatic control system a reliable source of data. The stability of the automatic control system is also greatly influenced and limited by the accuracy of the sensors in the system. Therefore, it is crucial for practical reasons that the autonomous control system can immediately identify and assess sensor problems. The creation of manufactured goods to achieve the highest quality requires the use of various sensors to monitor and real-time alter various process parameters gathered throughout the production process so that the field machinery and equipment function in a stable and dependable condition or the best state. As a result, the use of sensors in automation systems plays a crucial role. The precision with which on-site sensor data is detected will have an immediate impact on the effectiveness of the automation control system and the achievement of the function. Once the sensor data is incorrect or aberrant, it will immediately result in the automated control function failing, which will substantially result in equipment damage or production line failure [2, 3].

In this paper, we use multi-sensor data fusion technology to monitor and identify the status of sensors in the system, to detect the sensor's fault in time, and to improve the reliability and stability of the automatic control system by using a fault-tolerant control strategy [4]. The current research is less on the problem of fault-tolerant control of the system in case of sensor failure. The fault diagnosis method for unipolar modulation and the fault-tolerant control effect still needs to be improved. According to the above problems, the following contributions are made in this paper. (I) The study takes the load mutation factor into account when conducting experimental verification of fault diagnosis and fault-tolerant control. The overall results are optimized and more accurate control effects are obtained. (II) A method for fault detection and control reconfiguration of single-phase PWM rectifier sensors is suggested. Based on a powerful robust sliding mode observer for sensor fault detection using an analytical redundancy technique, a quick and trustworthy fault-tolerant control method is developed. (III) An active fault-tolerant control method based on filtered state feedback and multi-step predictive state feedback with dual fault-tolerant controller switching is designed to ensure good fault tolerance and dynamic performance of the closed-loop system in the case of sensor faults. The effectiveness of the proposed strategy is verified by simulation and experiment.

2. Important sensor components and failures

The sensor is separated into the following sections via the detecting principle [5]. The components are the sensitive element, the conversion element, the transformation circuit, the output standard signal, and the auxiliary power source that powers the aforementioned components as shown in Fig. 1.

Sensors are susceptible to temperature, environmental, and other factors that cause their signal instability because they are internally packaged with electronic components and some sensor installation sites are very harsh high temperatures and humidity and vibrating. Since sensors work for a long time in the above harsh environment is easy to achieve abnormal problems, e.g., aging, broken wires, etc., which will cause the sensor detection output signal instability. This will make the associated sensor detection condition seem strange. The automated control system will eventually lose a stable and reliable source of data, which will result in control failure and abnormal control functions, which will then send the production line's pile of steel and other phenomena, causing serious damage to the rolling line equipment. This detection state of the abnormal sensor will not be able to detect the monitored equipment status information.

The faulty sensor should be promptly and accurately identified by the system [6], reasonably protected by the automated control system, and can be effectively diagnosed and isolated using fault-tolerant control technology, so that equipment with or without sensors can operate steadily, safely, and reliably. This is necessary to avoid the issue of equipment control failure caused by abnormal sensor detection.

It is crucial to understand how the corresponding automatic control system can achieve safe and stable control after sensor state monitoring and fault detection [7, 8]. This involves two key issues: the first is the issue of fault identification following abnormal sensor state abnormality; the second is the fault tolerance mechanism and the corresponding stable control method after fault identification, i.e., fault-tolerant control. The fault tolerance, stability, and reliability of the entire control system can be increased, losses can be reduced, and the automated production line can play a safe and stable production security role only after the timely and effective identification of the abnormal sensor state signal information. Based on the identification of the abnormal signal using the corresponding fault tolerance mechanism.

3. Sensor status detection and fault identification

To ensure the accuracy of the sensor signal, the sensor operating status must be monitored to ascertain whether it is normal and to forecast the diagnosis of equipment failure and troubleshooting. By effectively monitoring the sensor's state, the automatic control monitoring system can identify and determine the field sensor's operating status, using a variety of discriminatory techniques. To effectively assess the field equipment's state of operation, a comprehensive judgment of the sensor state is normal or abnormal, and display and record the state, and abnormal state of the alarm, for the sensor equipment state failure analysis, performance evaluation, and logical use of effective information. This can be done by combining the historical state of sensor operation with the current actual situation. The use of advanced field sensor technology, through efficient monitoring methods, sensor detection output data processing, and data results transmission to the database for storage, extraction of characteristic information, identification of faults, and provision of scientifically sound, economically sound preventative and corrective measures or maintenance programs, constitute the core of sensor condition monitoring technology.

There are three basic components to the condition monitoring and problem diagnostic system [9, 10]. The three processes of field data collecting, sensor status monitoring, and sensor self-fault diagnosis may be explained as follows. The monitoring of the sensor state is both the extension and automatic realization of the field data acquisition function as well as the premise and basis for the diagnosis of the sensor's fault. The field data acquisition serves as the foundation for ensuring accurate monitoring and diagnosis of

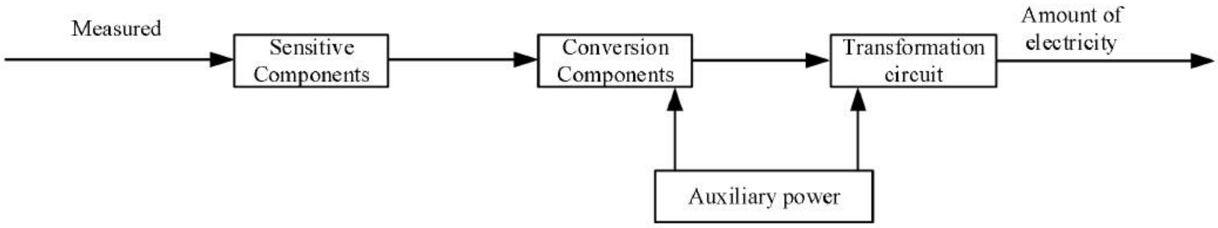


Fig. 1. Composition of the sensor.

the sensor state. The basis of the sensor condition monitoring system is the fault diagnosis of the sensor itself, and the three components work in concert to provide a whole condition monitoring and fault diagnostic system as shown in Fig. 2.

The duties of the data acquisition component include signal pre-processing, filtering and limiting, unit conversion, and signal acquisition of analog and switching signals [11, 12]. By using multiple sensor data resources in the field, combining the data information from these multiple sensors in space and time. Effectively combining the sensor information that can achieve redundancy or complementarity, and effectively differentiating and classifying the status of the field sensors, the condition monitoring part's task is to obtain a consistent interpretation or description of the subject) based on the front-end data acquisition.

A valid and realistic assessment for the condition of these field sensor devices will eventually be achievable. The following is a list of the specific material in this section. The analysis of sensor data signals [13], including front-end sensor processing of raw data, back-end fault diagnostics, numerical exceedance analysis, historical data statistical analysis, timing analysis, automatic trigger sound, and light alert [14]. To use the appropriate safety fault-tolerant control strategy after the fault diagnosis, it is possible to determine whether the sensor fault diagnosis part has returned to the normal working state based on the reasonable and effective monitoring of the state of the equipment status information.

The capture of equipment fault signals [15], feature extraction from those signals [16], and pattern categorization of equipment problems make up the diagnostic process. In conclusion, the data fusion technology is mostly used in fault diagnosis systems based on multi-sensor data fusion to increase fault detection precision (as shown in Fig. 3).

To collect the problematic device status will immediately fuse the multi-sensor data. The information from each sensor should be examined from a variety of angles throughout the multi-sensor data level fusion process. The consistency of the data after data fusion may be assessed by determining if the original sensor data are correlated.

4. Fault-tolerant controller design for sensor failures

4.1. Problem description

The model of a nonlinear stochastic discrete system with linear output is as follows in the event of sensor failure.

$$x = f(x) + Bu + \mathbf{\Gamma} v \tag{1}$$

$$y = c\boldsymbol{x} + J\alpha_t + \boldsymbol{w} \tag{2}$$

where $x \in R^n$ represents the state vector of the system, $\boldsymbol{u} \in R^p$ denotes the control input, $y \in R^m$ defines the sensor output $\mathbf{\Gamma} \in R^{n\times p}$, p and m represent the p and m dimensional Gaussian white noise vectors, respectively, J represents the sensor fault magnitude, and α_t denotes the unknown time function. characterizes the temporal properties of the fault.

The concept of the fault-tolerant control based on filtered state feedback is to design a fault-sensitive controller switching conditions and try to eliminate the effects of faults in the state prediction to achieve an asymptotic estimate of the true state under faults. The concept of fault-tolerant control based on multi-step predictive state feedback is to design fault-sensitive controller switching conditions. Therefore, the sensor errors are tolerated by the closed-loop system based on filtered state data and multi-step predictive state feedback.

The system state variables are frequently used in fault diagnosis to identify the operating conditions of the system and to enhance the control performance of actual control systems. Since the majority of these state variables cannot be measured directly, which is crucial to correctly estimate diagnose error. The estimated values of directly, which is crucial to correctly estimate diagnose error. The estimated values of the state variables $\hat{x}(k+1/k+1)$ and the subsequent forecasted values $\hat{x}(k+1/k)$ for nonlinear stochastic discrete systems may be achieved in this study using the extended Kalman filter's filtering approach.

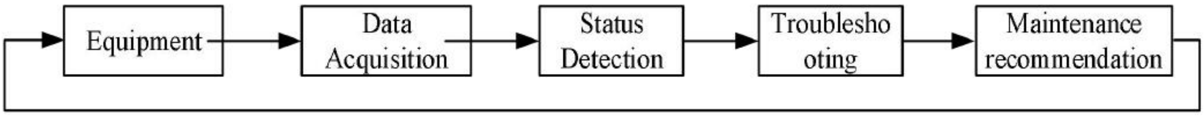


Fig. 2. Sensor detection system.

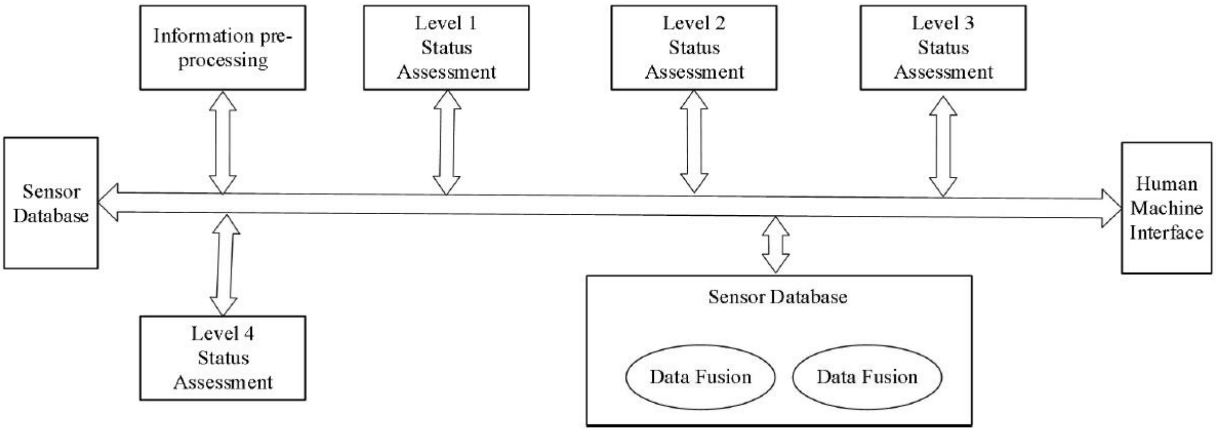


Fig. 3. Functionality of sensor data fusion.

4.2. Compensator design for sensor multiplicative faults

Based on the estimation of the system state by the extended Kalman filter, the sequence of residuals is defined as $\gamma(k) = y(k) - \hat{y}(k/k) = y(k) - c\hat{x}(k/k))$. The residual sequence $\gamma_i(k)$ meets the system's requirements while it is operating normally. $\gamma : N\left(0, \sigma_i^2\right)$. Where $\mu_{i1}(k)$ will greatly depart from 0 and $\gamma_i(k)$ will not meet the $\gamma : N\left(0, \sigma_i^2\right)$ distribution. When there is an anomaly, the real mathematical expectation can be adjusted to the following equation,

$$d_i(k) = \frac{\sigma_{i0}^2(k)}{\sigma_i^2} - \ln\frac{\sigma_{i1}^2(k)}{\sigma_i^2} - 1 \tag{3}$$

where $\sigma_{i0}^2(k)$ is the variance at the best possible mathematical expectation. The variance at the actual mathematical expectation is represented by $\sigma_{i1}^2(k).i = 1, 2, \cdots, l$ indicates the i-th sensor. When a defect occurs, $\mu_{i1}(k)$ will considerably depart from $0, \sigma_{i0}^2(k)$ will greatly diverge from d, and $\sigma_{i1}^2(k)$ the change is not statistically different. As a result, it is understood that the defect's impact is amplified in $d_i(k)$, and the existence of the fault may be determined by passing judgment on $d_i(k)$. The representation that follows is then available.

$$\begin{aligned} H_0 &: d_i(k), \beta_i \\ H_1 &: d_i(k) > \beta_i \end{aligned} \tag{4}$$

where β_i denotes the threshold value. By assuming that the sensor is fault-free and the system is functioning correctly at an instant $k_f - N - 1$, the counterfactual approach can be applied. As a result, the sensor's output value at $k_f - N - 1$ moments may be utilized to determine the multiplicative fault magnitude. To counteract the system impact of a sensor defect, the estimated value of the Kalman filter is also adjusted. Each state estimate needs to be adjusted since a sensor malfunction will affect them all due to the delay between the system and the filter model as well as the diagnostic connection.

$$\hat{f}(k) = y(k) - y\left(k_f - N - 1\right) \tag{5}$$

$$\hat{\gamma}(k+1) = \gamma(k+1) - \hat{f}(k) \tag{6}$$

$$\hat{x}(k+1/k+1) = \hat{x}(k+1/k) + K(k+1)\hat{\gamma}(k+1) \tag{7}$$

4.3. Fault-tolerant controller design based on state feedback

$$A = A_1 + A_2 \tag{8}$$

Suppose that for a certain initial state x_0, there exists an equilibrium point x_b of the system, the estimation of the system state using the extended Kalman filter is such that the state feedback is $u(k) = \boldsymbol{H}\hat{x}(k/k) + \boldsymbol{G}$, where H and G are a constant coefficient array of the corresponding dimension. Let the equation $A_1 = \frac{\partial f}{\partial x}(x)\Big|_{x=x_b}$, $A_2 = \frac{\partial(Bu)}{\partial x}(x)\Big|_{x=x_b}$

From the Kalman filter, we know that $\hat{x}(k/k) \rightarrow x(k)$. The following equation is obtained.

$$\boldsymbol{A}_2 = \left.\frac{\partial(Bu)}{\partial x}(x)\right|_{x=x_{\hat{b}}} = \left.\frac{\partial(BH\hat{x})}{\partial x}(x)\right|_{x=x_b} \approx \left.\frac{\partial(BHx)}{\partial x}(x)\right|_{x=x_{\hat{b}}} \tag{9}$$

According to the stability theorem for nonlinear systems, when all eigenvalues of A satisfying $\operatorname{Re}\lambda_i < 0$, then the system is asymptotically stable concerning that equilibrium point.

Taking a two-dimensional system as an example, suppose $\boldsymbol{B} = \begin{bmatrix} 0 \\ B_2 \end{bmatrix}$, $\boldsymbol{A}_1 = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}$ and $\boldsymbol{H} = \begin{bmatrix} H_1 & H_2 \end{bmatrix}$ can be derived that.

$$\boldsymbol{A} = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} + B_2H_1 & A_{22} + B_2H_2 \end{bmatrix} \tag{10}$$

$$\lambda_{1,2} = \frac{A_{11} + A_{22} + B_2H_2 \pm \sqrt{V}}{2} \tag{11}$$

All the eigenvalues were obtained after the calculation λ_i. Among them $V = (A_{11} + A_{22} + B_2H_2)^2 - 4\left(A_{11}A_{22} + A_{12}A_{21} + A_{11}B_2H_2 + A_{12}B_2H_1\right)$. When $\lambda_i < 0$:

$$\begin{cases} A_{11} + A_{22} + B_2H_2 < 0 \\ (A_{11} + A_{22} + B_2H_2)^2 - \\ 4\left(A_{11}A_{22} + A_{12}A_{21} + \right. \\ \left. A_{11}B_2H_2 + A_{12}B_2H_1\right) < 0 \end{cases} \tag{12}$$

To further simplify the Eq.(12), and the Eq.(13) can be achieved.

$$\begin{cases} H_2 < -\left(A_{11} + A_{22}\right)/B_2 \\ H_1 > \left[A_{11} + A_{22} + B_2H_2\right)^2/4 - \\ A_{11}A_{22} - A_{12}A_{21} - A_{11}B_2H_2\right]/A_{12}B_2 \end{cases} \tag{13}$$

When the state feedback gain matrix is satisfied, the system is stable. And then according to the system control performance requirements to determine the constant term G, you can get the state feedback controller $u = \boldsymbol{H}\hat{x} + \boldsymbol{G}$.

The controller must be modified once a system failure is identified. Currently, utilizing the corrected state estimates provided in the previous paragraph and the aforementioned controller design methodology, fault-tolerant regulation of the system for sensor defects may be achieved. This approach is only suitable for sensor multiplicative errors because of the delay in the fault diagnosis link, and the system control performance will suffer as a result of the fault and controller switching.

4.4. Fault-tolerant control method based on multi-step predictive state feedback

After a sensor defect, the system state overshoots significantly as a result of the fault's influence and the switching of the control law, which has some impact on the control system's quality. The one-step prediction estimate $\hat{x}(k+1/k)$ of the filter is unaffected by the sensor fault and its estimate is acceptable, while the state estimate $\hat{x}(k+1/k+1)$ of the filter may be considered to be deviating from the state estimate range due to the sensor fault when a specific threshold value is exceeded at a specific moment $[\hat{x}(k+1/k+1) - \hat{x}(k+1/k)]^2$. The state estimation principle may thus be applied for multi-step prediction estimation of the system state based on the one-step accurate prediction estimate $\hat{x}(k+1/k)$ of the filter.

$$\hat{x}(k+2/k) = f(k, u(k), \hat{x}(k+1/k)) \tag{14}$$

$$\hat{x}(k+3/k) = f(k, u(k), \hat{x}(k+2/k)) \tag{15}$$

$$\hat{x}(k+n/k) = f(k, u(k), \hat{x}(k+n-1/k)) \tag{16}$$

To minimize the overshoot impact of the sensor defect on the system state, a feedback controller based on a multi-step predictive estimate sweet day $\boldsymbol{u} = \boldsymbol{H}\hat{x}(k+n/k) + \boldsymbol{G}$ is designed and utilized to operate the system in place of the original controller. The fault diagnosis link will locate and identify the fault during the brief period of the alternative control, and the fault-tolerant control link will respond appropriately. The system controller will convert from a fault-tolerant controller based on extended Kalman filter state feedback to a feedback controller based on a multi-step prediction estimate when $[\hat{x}(k+1/k+1) - \hat{x}(k+1/k)]^2$ falls below a certain threshold, assuring the system's dynamic performance. However, because this method does not correct the state estimation results of the multi-step prediction to eliminate the influence of sensor failure on the estimation, the accuracy of state estimation is reduced. As a result, this fault-tolerant control scheme must sacrifice system performance to ensure that the system can still operate safely when sensor failure occurs.

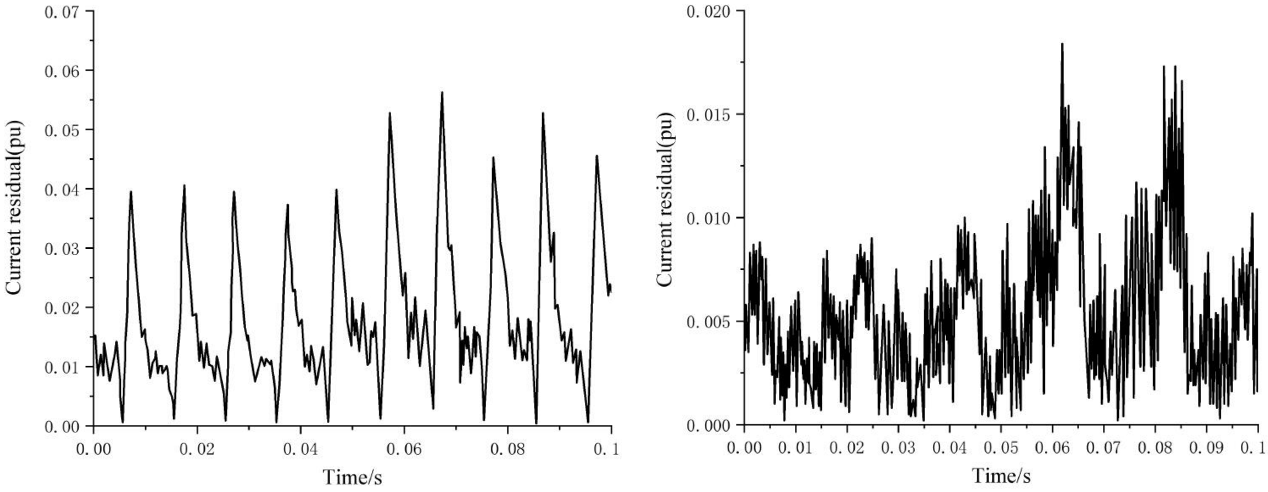
5. Results and discussions

The simulation of fault-tolerant control was performed on a computer. This computer was set up with the following parameters: Equipped with an Intel(R) Core(TM) i5-94002.8GHz processor and 8GB of RAM. A continuously stirred kettle reactor was selected and the following equation was obtained after discretization

$$\begin{bmatrix} \dot{x}_1(k+1) \\ \dot{x}_2(k+1) \end{bmatrix} = \begin{bmatrix} x_1(k) \\ x_2(k) \end{bmatrix} + \mathrm{d}tg \begin{bmatrix} -x_1 + D_\alpha\left(1 - x_1\right)\exp\left(\frac{x_2}{1+x_2/r}\right) \\ -x_2(1+\beta) + HD_\alpha\left(1 - x_1\right) \times \\ \exp\left(\frac{x_2}{1+x_2/r}\right) + \beta U \end{bmatrix} + \Gamma(k)v(k) \tag{17}$$

$$y(k+1) = Cx(k+1) + w(k+1) \tag{18}$$

where $\mathrm{d}t$ Indicates the sampling interval, $v(k) \in R^2, w(k) \in R^2$ denotes mutually independent Gaussian white noise



(a) Current residuals.

(b) DC-side current residuals.

Fig. 4. System residual waveform during normal sensor operation

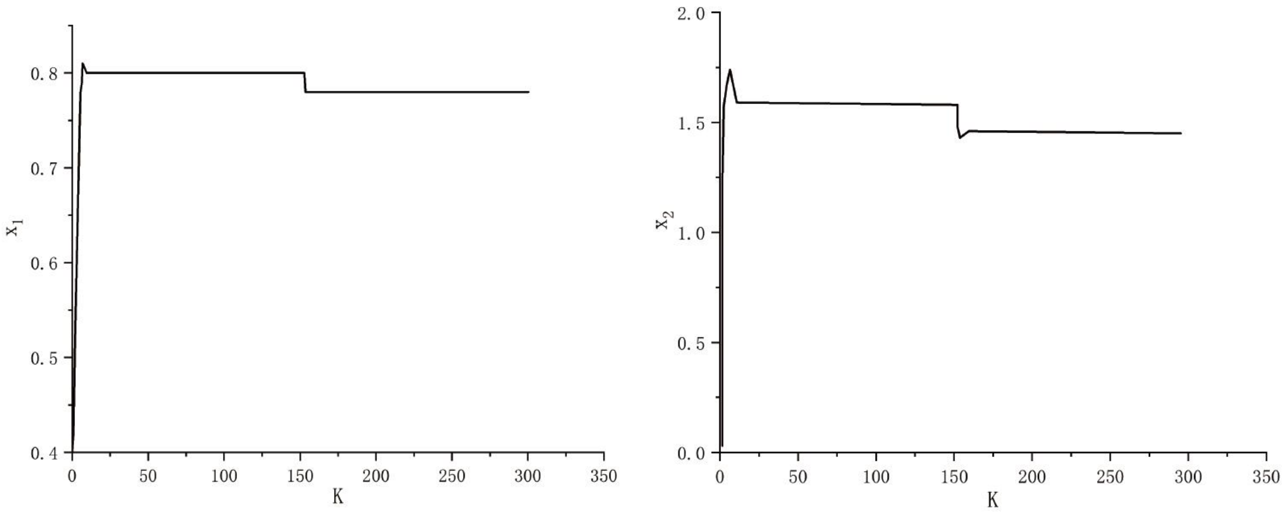


Fig. 5. Variation curves of system states x_1 and x_2 when no fault-tolerant control link is added.

with zero mean. Their covariance is $Q(k)$ and $R(k)$, respectively. The parameters of CSTR are $r = 13.4, H = 2.5, D_\alpha = 1.0, \beta = 0.5, T_f = 0.75\,\mathrm{K}$, $\mathrm{d}t = 0.15\,\mathrm{s}$, $C = \begin{bmatrix} 1 & 0 \\ 0 & 0.75 \end{bmatrix}$, $\mathbf{\Gamma}(k) = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$, $Q(k) = \begin{bmatrix} 0 & 0 \\ 0 & 0.0001/\mathrm{d}t \end{bmatrix}$, $R(k) = \begin{bmatrix} 1/2500 & 0 \\ 0 & 0.001 \end{bmatrix}$.

The initial parameters of the estimated model are respectively $\hat{x}_1(1) = 0$, $\hat{x}_2(1) = 0$ corrected to $\sigma^2 = 0.005^2, N = 10, \beta = 1000$. The initial state of the system. $x_1(1) = 0.4, x_2(1) = 0$. To find the coordinates of the equilibrium point of the system, $x_{1\,\mathrm{b}} = -0.1279$ and $x_{2\,\mathrm{b}} = -0.4281$ be ensured. The control inputs based on state estimation feedback can be designed. $U(k) = [-70 - 24.5]\hat{x}(k/k) + 94.15$, At this point, the eigenvalue of A is $\lambda_{1,2} = -0.0048 \pm 0.0983i$, system stability. When $[\hat{x}(k+1/k+1) - \hat{x}(k+1/k)]^2 > 0.0001$, based on a multi-step prediction estimate, the system employs feedback control. For the specified initial values, the control input based on multi-step predictive estimation feedback may be derived: $U(k) = [-70 - 24.5]\hat{x}(k+n/k) + 65.835$, system stability.

A sudden load change is simulated at t=0.05s, and the equivalent load resistance is switched from 230 to 180. The host computer then gathers the current and voltage residuals, and the waveforms are displayed in Fig. 4 when both the net-side current and DC-side voltage sensors are functioning normally, during typical sensor operation, the current and voltage residuals are kept below 0.05 and 0.02,

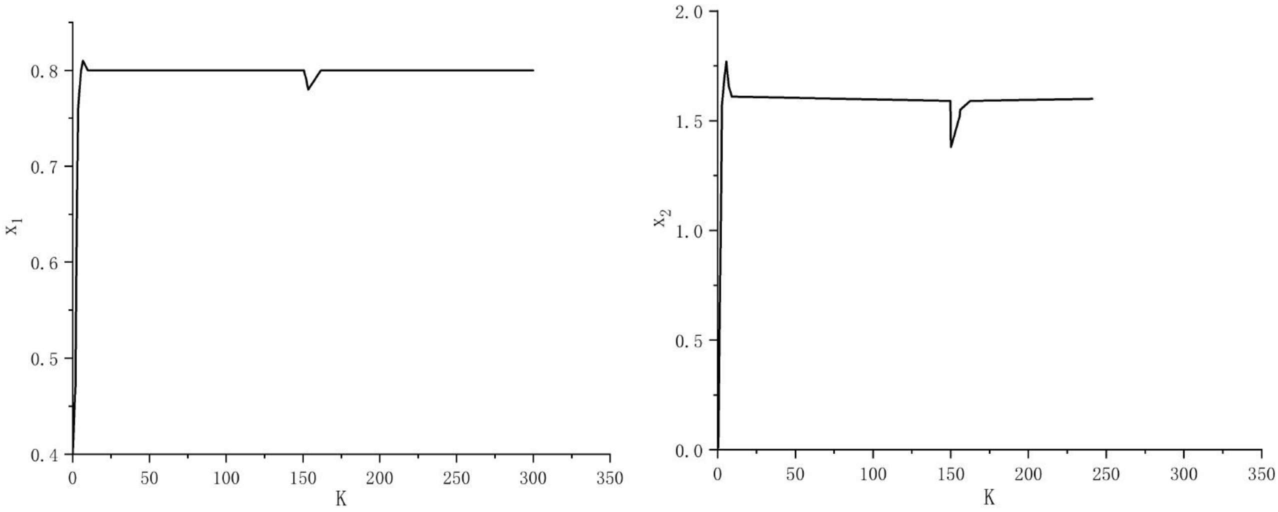


Fig. 6. Curves of system states x_1 and x_2 under the action of fault compensation and control law reconfiguration.

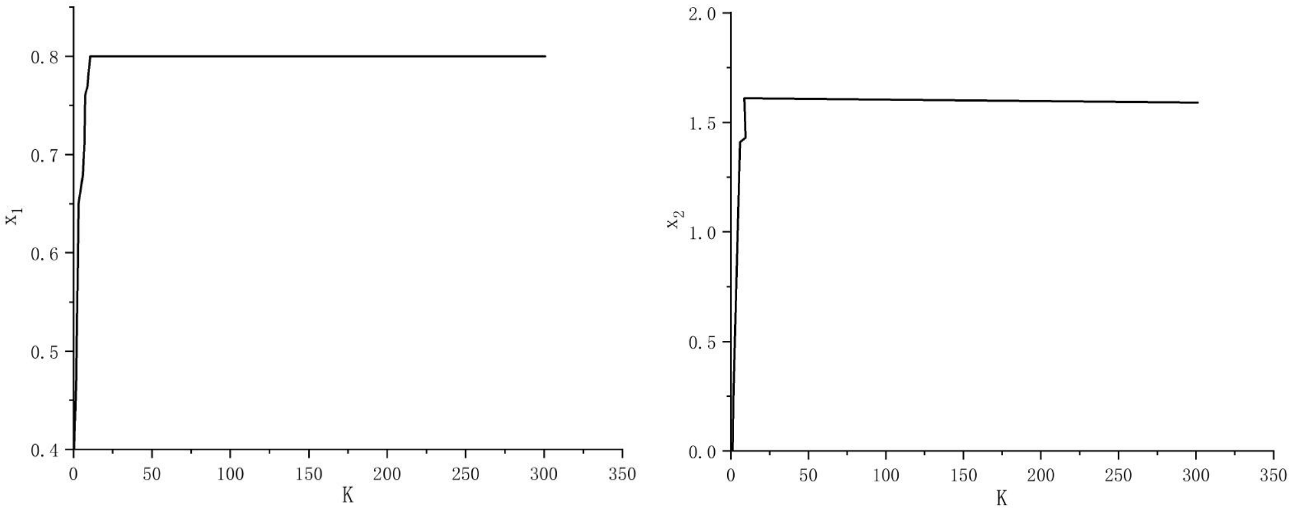


Fig. 7. Change curves of system states x_1 and x_2 under the action of double fault-tolerant controller switching.

respectively. Since the system residuals are normalized, the residuals only slightly rise after the abrupt load shift, and no misdiagnosis takes place.

The above Fig. 4 shows the residual waveform of the system during normal sensor operation. When a current sensor open-circuit fault occurs, the residual waveform immediately increases. The fault diagnosis unit quickly locates the faulty sensor and changes the system. The net-side current stabilizes after about 3 frequency cycles of small adjustment, and the net-side current and DC-side voltage amplitude gradually increase. This is because the observed current, rather than the sensor acquisition value for the current loop closed-loop control, is used as the feedback value in the system reconfiguration. As a result, the current observation error enters the double closed-loop control system and amplifies it, bringing the steady-state error of the network-side current and DC-side voltage values, but it has no impact on the network-side unit power factor control and the overall system stability. The fault detection unit finds the problematic sensor after about 2.5 milliseconds, and the waveform of the current sensor gain anomaly fault is identical to that of the open-circuit fault. After the fault-tolerant control approach is implemented in response to the voltage sensor error, the network-side current amplitude is slightly raised while the DC-side voltage stabilizes around the specified value. The aforementioned experimental findings demonstrate that the suggested fault diagnostic and fault-tolerant control technique works as intended.

At $k = 150$, concentration sensor 1 experiences a multiplicative error, which causes the gain to increase to $0.85S_{1\infty}$. ($S_{1\infty}$ represents the average steady-state output of sensor 1 during typical process operation $S_{1\infty} = 0.8$). As illustrated in Figs **??**, the system state changes at this point as a result of the fault-tolerant controller switching, the fault compensation and control law reconstruction switching, and the double fault-tolerant controller switching, respectively.

6. Conclusion

In order to improve the sensor failure when it causes a series of problems, the fault-tolerant control method of single fault diagnosis, compensation, and control law reconstruction in this paper has the proactiveness of active fault-tolerant control, which can guarantee the control performance of the system in the case of multiplicative sensor failure; while the fault-tolerant control method based on multi-step predictive state feedback has the conservativeness of passive fault-tolerant control at the expense of system performance, which makes the system less reliable. The fault-tolerant control method based on multi-step predictive state feedback has the conservative nature of passive fault-tolerant control at the expense of system performance, allowing the system to have good dynamic performance despite sensor failure. The dual fault-tolerant controller switching method designed in this paper has the advantages of both ensuring good fault-tolerant control performance and dynamic performance of the system and achieving fault-tolerant control of sensor failure. Since the switching conditions of the fault-tolerant controller in this method are sensitive to faults based on multi-step predictive state feedback, the method is also applicable to additive sensor faults. The next step will be to consider multiple fault-tolerant control sensor methods to achieve fault-tolerant performance and stability of the system.

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