

文章编号: 1000-8055(2012)06-1432-09

Fault diagnosis and isolation of the component and sensor for aircraft engine

QIU Xiao-jie, HUANG Jin-quan, LU Feng, LIU Nan

(College of Energy and Power Engineering,

Nanjing University of Aeronautics and Astronautics, Nanjing 210016, China)

Abstract: Aircraft engine component and sensor fault detection and isolation approach was proposed, which included fault type detection module and component-sensor simultaneous fault isolation module. The approach can not only distinguish among sensor fault, component fault and component-sensor simultaneous fault, but also isolate and locate sensor fault and the type of engine component fault when the engine component fault and the sensor faults occur simultaneously. The double-threshold mechanism has been proposed, in which the fault diagnostic threshold changed with the sensor type and the engine condition, and it greatly improved the accuracy and robustness of sensor fault diagnosis system. Simulation results show that the approach proposed can diagnose and isolate the sensor and engine component fault with improved accuracy. It effectively improves the fault diagnosis ability of aircraft engine.

Key words: aircraft engine; sensor fault; engine component fault; simultaneous fault; diagnosis; isolation; double-threshold mechanism

CLC number: V233.7

Document code: A

The requirement of high performance and the increased complexity of aircraft engine result in the fault rate increased, with the continuous development of aircraft engine technology. The development of fault diagnosis technology is the key way to improve the reliability and safety and to reduce maintenance costs of aircraft engines^[1-3]. For the engine working environment is very severe, engine sensors and components are likely to fail or even fail simultaneously during operation. The different types of faults interact their diagnosis results, resulting in misdiagnosis or missed diagnosis by fault diagnosis system. Therefore, it is necessary to research fault diagnosis and isolation of aircraft engine component and sensor. The diagnostic threshold directly affects the performance of diagnostic system. Setting the threshold at a low value increases the

chance of detecting faults, however, also increases the chance of generating false alarms. Conversely, setting the threshold at a high value decreases the chance of generating false alarms but also decreases the chance of detecting faults. Research on diagnosis threshold has critical engineering meaning.

Currently, Kalman filter approach is widely used in aircraft engine component and sensor fault diagnosis^[4-10]. An approach to aircraft engine sensor fault diagnostics was addressed by Merrill et al.^[8] through utilization of a bank of Kalman filters. This work was later extended by Kobayashi et al.^[9] to account for not only sensor faults but also engine component faults; LU et al.^[10] improved the fault diagnosis accuracy using fusion approach based on Kalman filter approach and other diagnostic approaches. The ap-

Received: 2011-06-30

URL: http://www.cnki.net/kcms/detail/11.2297.V.20120704.1152.201206.1432_032.html

Foundation item: Program Sponsored for Scientific Innovation Research of College Graduate in Jiangsu Province(CX10B_108Z)

E-mail: qzhang6008@yahoo.cn

proaches used above in fault diagnosis and distinction of aircraft engine component and sensor had achieved good effects, but they cannot solve simultaneous engine component and sensor faults diagnosis or the fault positioning. Previous literatures choose fault diagnostic threshold choice were using single-threshold method, and not select threshold according to the engine condition or the sensor actual situation. Few reports about the threshold choice analysis can be found.

In this paper, the fault diagnosis and isolation approach on aircraft engine component and sensor using the Kalman filter has realized the engine component and sensor fault distinguish and also realized the simultaneous fault isolation and positioning of engine component fault and sensor fault. The double-threshold mechanism is designed on the bases of analyzing the sensor output weight sum of squared residuals and the statistic characteristics of each sensor at different conditions. It is also to select the thresholds of the fault diagnosis system according to engine conditions and sensor types.

1 Fault diagnosis and isolation principles of engine component and sensor

The aircraft engine component and sensor fault diagnosis and isolation approach consists of fault type detection module and component-sensor simultaneous fault isolation module.

Fault type detection module is to judge the current fault type: the sensor fault or engine

component fault or component-sensor simultaneous fault. If it is sensor fault or component fault, then sensor fault location or component fault type and degree can be diagnosed. If it is component-sensor simultaneous fault, only the alarm could be given. In this case, it can not give the exact fault isolation or diagnostic conclusion.

Component-sensor simultaneous fault isolation module is to judge the sensor fault location and the type of engine component fault when it is component-sensor simultaneous fault.

Aircraft engine component and sensor fault diagnosis and isolation approach is shown in Fig. 1.

1.1 Fault type detection module

The fault type detection module consists of $n+1$ Kalman filters for system, n is the number of sensors, the first n Kalman filters for the n sensors and the $(n+1)$ th Kalman filter for the engine components. Kalman filter output fault indication signal is denoted as $W_{ssr,i}$ (weight sum of squared residuals, $i=0,1,\dots,n$) for the i th sensor:

$$W_{ssr,i} = (\Delta e_i)^T (\text{diag}[\sigma_i]^2)^{-1} (\Delta e_i) \quad (1)$$

In Eq. (1), $\Delta e_i = \Delta y_i - \Delta \hat{y}_i$, Δy_i is a sub-set of the output vector which remove the i th value, $\Delta \hat{y}_i$ is the corresponding sub-set of the filtering output vector, σ_i is the corresponding standard deviation of sensor noise. The sensor fault is identified by comparing the signal of $W_{ssr,i}$ with the corresponding threshold.

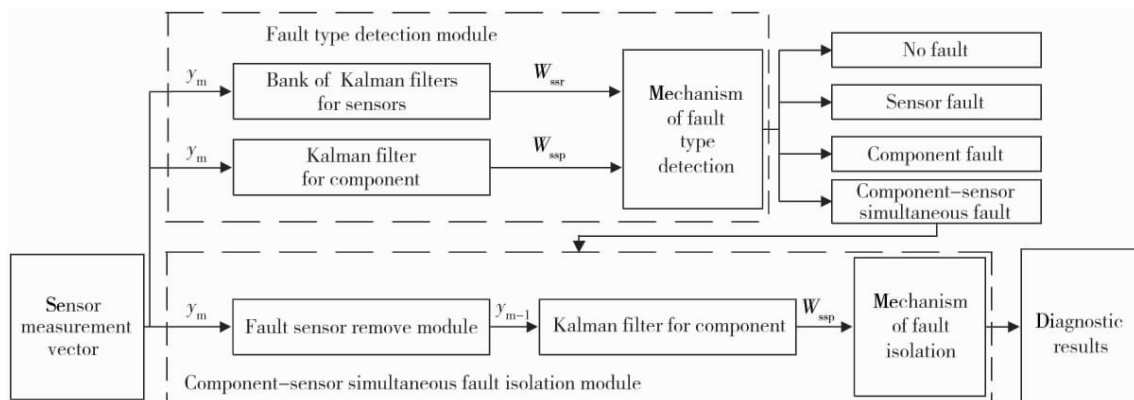


Fig. 1 Fault diagnosis and isolation approach for the component and sensor of aircraft engine

Similar to the sensor Kalman filter, the output fault indication signal W_{ssk} of engine component Kalman filter is as below:

$$W_{ssk} = (\Delta e)^T (\text{diag}[\sigma]^2)^{-1} (\Delta e) \quad (2)$$

In order to distinguish engine component fault from sensor fault, the fault indicator signal W_{ssk} should: 1) remain small in the case of component faults and 2) increase in the case of a sensor fault. But in the actual process, it is true in the first situation, but not in the second one. In the case of sensor failure, the W_{ssk} remains small for some case. For this case, it was found that, the W_{ssk} remains small because Kalman filter adjusts the engine health parameters. Therefore, the value of W_{ssk} can not distinguish the sensor fault from the engine component fault. In order to settle this shortcoming, another fault indicator signal is added. This signal, a weighted sum of squared tuners (W_{ssp}), is defined as follows:

$$W_{ssp} = w(\Delta p)^T (\Delta p) \quad (3)$$

In Eq. (3), w is the weight. Δp is degeneration of the engine component health parameter vector.

According to the definition, the fault indication signal W_{ssp} increases for both sensor fault and engine component fault. However, W_{ssp} increase little for component fault but a lot for sensor fault. Therefore, the fault type detection mechanism is proposed as follows:

1) If all the $W_{ssr,i}$ values are below the fault detection threshold and W_{ssp} is below the first layer threshold, it suggests no fault occur;

2) If all the $W_{ssr,i}$ values are over the fault isolation threshold and W_{ssp} is between the first and second layer thresholds, it suggests a engine component is in faulty;

3) If only one $W_{ssr,i}$ value is below the fault detecting threshold, the other $(n-1)$ $W_{ssr,i}$ values are over the fault isolation threshold and W_{ssp} is over the second layer threshold, it suggests a sensor is in faulty;

4) If all the $W_{ssr,i}$ values are over the fault isolation threshold, and W_{ssp} is over the second layer threshold, it suggest there is a serious engine component fault or component-sensor simultaneous

ultaneous fault occur. If it is a serious engine component fault, then the fault can be isolated by the results of health parameters estimation. If it is a component-sensor simultaneous faults, this mechanism can only give an alarm.

The detection threshold and isolation threshold of the sensor fault indicator signal $W_{ssr,i}$ will be given in detail in section 3. The threshold of component fault indicator signal W_{ssp} is determined by the weight w and the fault definition of a component fault Δp_i . If $\Delta p_i = p_1$ is considered to be a component fault, the first layer threshold of W_{ssp} is defined as $\lambda_{c1} = w \times p_1^2$. If $\Delta p_i = p_2$ is considered to be a serious component fault, the second layer threshold of W_{ssp} is defined as $\lambda_{c2} = w \times p_2^2$.

1.2 Component-sensor simultaneous fault isolation module

According to the fault type detection module, when engine component fault and sensor fault occur simultaneously, only alarm can be given, and the fault location can not be isolated. The engine component-sensor fault simultaneously isolation module is designed to add a fault sensor remove module before the Kalman filter for engine components in Fig. 1. In the fault sensor remove module, the i th sensor value is removed and $W_{ssp,i}$ is calculated using the rest $n-1$ sensors information. If the fault-free sensor value is removed, the rest $n-1$ sensors information still contains the fault sensor information and fault component information. Therefore, the $W_{ssp,i}$ value did not generate significant changes comparing to W_{ssp} value of n sensors. If the fault sensor value is removed, the rest $n-1$ sensors information only contains the engine component fault information. Therefore, the $W_{ssp,i}$ value will be the smallest comparing to the other $W_{ssp,j}$ value ($j=1, \dots, n; j \neq i$), and lower than the second layers threshold. Based on this phenomenon, the fault isolation mechanism of component-sensor simultaneous fault is:

1) If the $W_{ssp,i}$ value is the smallest comparing to the other $W_{ssp,j}$ value ($j=1, \dots, n; j \neq i$),

and lower than the second layers threshold, it suggests the i th Sensor is in faulty;

2) The fault sensor value is removed and the component health parameters are estimated using the rest $n-1$ sets sensor information, then the engine component fault can be located.

2 To determine the threshold of sensor fault diagnosis

The sensor fault diagnostic threshold directly affects the performance of diagnostic system. Setting the threshold at a low value increases the chance of detecting faults but also increases the chance of generating false alarms. Conversely, setting the threshold at a high value decreases the chance of generating false alarms but also decreases the chance of detecting faults. The ideal threshold needs to ensure diagnosing at any fault level and to be of zero misdiagnosis rates, but these two requirements are contradictory. Because a single threshold can not meet the demands, double-threshold mechanism is introduced to solve this problem as follows:

1) The threshold of the first layer is used for sensor fault detection, the system will give an alarm signal if $W_{ssr,i}$ values are over the fault detection threshold. This signal implies a sensor fault might be occurred.

2) The threshold of the second layer is used for sensor fault isolation, the system will suggest a sensor is in faulty if $W_{ssr,i}$ values are over the fault isolation threshold.

2.1 Determine the fault detection threshold

Fault detection threshold is determined by the statistical properties of fault indicator signal $W_{ssr,i}$ when all sensors are fault free. There are n sensors in all, and then the Kalman filter fault indicator signal $W_{ssr,i}$ without the i th sensor information can be expressed as:

$$W_{ssr,i} = \sum_{j=1, j \neq i}^n \frac{\gamma_j^2}{\sigma_j^2} \quad (4)$$

In Eq. (4), γ_j is the j th element of Δe , $\gamma_j \sim N(0, \sigma_j^2)$.

Define $z = \gamma_j^2$, then the probability density function of z is:

$$f(z) = \begin{cases} \frac{e^{-z/2\sigma_j^2}}{\sigma_j \sqrt{2\pi z}} & z > 0 \\ 0 & z \leq 0 \end{cases} \quad (5)$$

Denote the threshold of γ_j^2 as λ_{slj} , which is a fractals value of the statistical properties of γ_j^2 , then:

$$P\{\gamma_j^2 > \lambda_{slj}\} = \int_{\lambda_{slj}}^{\infty} \frac{e^{-z/2\sigma_j^2}}{\sigma_j \sqrt{2\pi z}} dz \quad (6)$$

Translate the Eq. (6) into $\chi^2(1)$ distribution. Define $z = \sigma_j^2 z'$, then:

$$P\{\gamma_j^2 > \lambda_{slj}\} = \int_{\lambda_{slj}/\sigma_j^2}^{\infty} \frac{e^{-\frac{z'}{2}}}{\sqrt{2\pi z'}} dz' \quad (7)$$

The constant value C_1 is obtained from $\chi^2(1)$ distribution table according to the value of α , then the threshold of γ_j^2 is $\lambda_{slj} = C_1 \sigma_j^2$. The value of the fault detection threshold is:

$$\lambda_{sl} = \sum_{j=1, j \neq i}^n \frac{\lambda_{slj}}{\sigma_j^2} = C_1 \times (n-1) \quad (8)$$

Through the analysis above, the sensor fault detection threshold only depends on the number of associated sensors. It is independent from sensor noise characteristics. That is, if no fault with the sensor, the sensor noise characteristics do not have effect on the fault indicator signal W_{ssr} .

2.2 Determine the threshold of fault isolation

As the sensor is in bad working environment, inevitably exists noise and slight deviations in the sensor value. According to the documents and institutes' experimental data^[11], when the sensor value deviation Δy_s is larger than a constant Δy_{fault} , the sensor is regarded failures. Fault isolation threshold is determined by the statistical properties of fault indicator signal $W_{ssr,i}$, which is calculated by the sensors' value with Δy_{fault} bias fault sensor. Define the f th sensor is in fault. There are n sensors in all, and then the Kalman filter fault indicator signal $W_{ssr,i}$ without the i th sensor information can be expressed as:

$$W_{ssr,i} = \left(\sum_{j=1, j \neq i, j \neq f}^n \frac{\gamma_j^2}{\sigma_j^2} \right) + \frac{\gamma_f^2}{\sigma_f^2} \quad (9)$$

In Eq. (9), $\gamma_j \sim N(0, \sigma_j^2)$, $\gamma_f \sim N(\Delta y_{fault}, \sigma_f^2)$, let $\gamma'_f \sim N(0, \sigma_f^2)$, then:

$$W_{ssr,i} = \left(\sum_{j=1, j \neq i, j \neq f}^n \frac{\gamma_j^2}{\sigma_j^2} \right) + \frac{(\gamma'_f + \Delta y_{\text{fault}})^2}{\sigma_f^2} =$$

$$\left(\sum_{j=1, j \neq i, j \neq f}^n \frac{\gamma_j^2}{\sigma_j^2} \right) + \frac{\gamma_f'^2}{\sigma_f^2} + \frac{2\Delta y_{\text{fault}} \gamma'_f}{\sigma_f^2} + \frac{(\Delta y_{\text{fault}})^2}{\sigma_f^2} \quad (10)$$

In Eq. (10), the threshold of γ_j^2 and $\gamma_f'^2$ is $C_1 \sigma_j^2$ and $C_1 \sigma_f^2$.

Define $\tau = \gamma'_f$, then the probability density function of τ is:

$$f(\tau) = \frac{1}{\sigma_f \sqrt{2\pi}} e^{-\frac{(\tau)^2}{2\sigma_f^2}}$$

$$(-\infty < \tau < \infty) \quad (11)$$

Denote the threshold of γ'_f as λ_{sf} , which is a fractals value of the statistical properties of γ'_f , then:

$$P\{\tau > \lambda_{sf}\} = \int_{\lambda_{sf}}^{\infty} \frac{1}{\sigma_f \sqrt{2\pi}} e^{-\frac{(\tau)^2}{2\sigma_f^2}} d\tau \quad (12)$$

Translate the Eq. (12) into $N(0,1)$ distribution. Define $\tau' = \tau/\sigma_f$, then:

$$P\{\tau > \lambda_{sf}\} = \int_{\lambda_{sf}/\sigma_f}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{(\tau')^2}{2}} d\tau' \quad (13)$$

The constant value C_2 is obtained from normal distribution table according to the value of α , then the threshold of γ'_f is $\lambda_{sf} = C_2 \sigma_f$. The value of the fault isolation threshold is:

$$\lambda_{s2} = (n-1) \times C_1 +$$

$$\frac{2C_2 \Delta y_{\text{fault}}}{\sigma_f} + \frac{(\Delta y_{\text{fault}})^2}{\sigma_f^2} \quad (14)$$

In the actual process, Δy_{fault} is a fixed value usually. The standard deviation of sensor noise changes with the condition of the engine and the sensor type. Therefore, the larger the standard deviation of sensor noise fault the smaller threshold value, and vice versa.

3 Simulation

A nonlinear component level model of turbofan engine is used for simulation in this paper^[12]. The engine operates in $H=0$ km, $Ma=0$. There are eight engine health parameters: fan efficiency η_f , fan flow ΔW_f , high pressure compressor efficiency $\Delta \eta_c$, high pressure compressor flow ΔW_c , low pressure turbine efficiency $\Delta \eta_{tl}$, low pressure turbine flow ΔW_{tl} , high pressure turbine efficiency $\Delta \eta_{th}$, high pressure turbine

flow ΔW_{th} ; and there are nine sensors in the engine model: fan spool speed N_f sensor, fan exit temperature T_{22} sensor, fan exit pressure p_{22} sensor, high pressure compressor spool speed N_c sensor, high pressure compressor exit temperature T_3 sensor, high pressure turbine inlet pressure p_4 sensor, high pressure turbine exit temperature T_{43} sensor, high pressure turbine exit pressure p_{43} sensor and low pressure turbine exit pressure p_5 sensor. The standard deviation of sensor noise in cruise and maximum thrust condition is shown in Table 1.

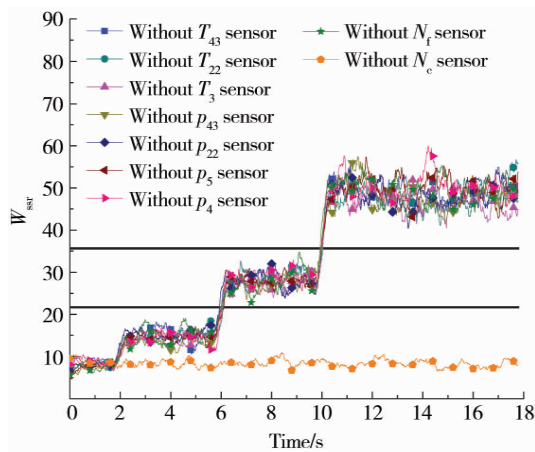
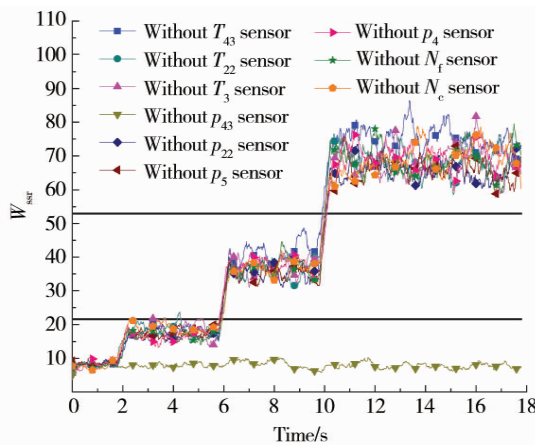
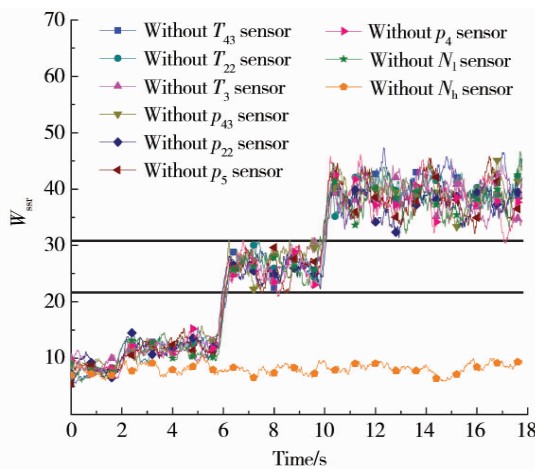
Table 1 Sensor noise standard deviation

	σ under cruise condition	σ under maximum thrust condition
N_f sensor	0.0015	0.002
N_c sensor	0.0015	0.002
T_{22} sensor	0.0011	0.0016
p_{22} sensor	0.0009	0.0015
T_3 sensor	0.0011	0.0016
p_4 sensor	0.0009	0.0015
T_{43} sensor	0.0011	0.0016
p_{43} sensor	0.0009	0.0015
p_5 sensor	0.0009	0.0015

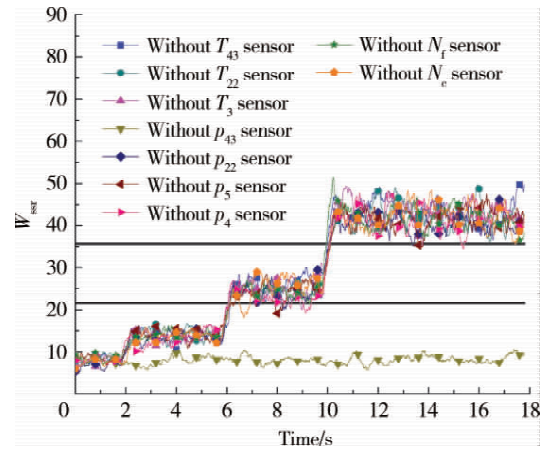
3.1 Simulation of sensor fault diagnosis based on double-threshold mechanism

Sensor bias faults of N_c and p_{43} in cruise condition and maximum thrust condition are simulated: no fault from 0 to 2 seconds, 0.3% disturbance from 2 to 6 seconds, 0.6% disturbance from 6 to 10 seconds, 1% bias fault after 10 seconds. The simulation results are shown in Figs. 2 to 5.

Set the N_c sensor bias fault in cruise condition as an example, (shown in Fig. 2), there are 9 sensors in this system, choose $\alpha=1$, calculate the fault detection threshold by the Eq. (8), $\lambda_{s1} = 21.7$, all fault indicator signals W_{ssr} do not exceed the fault detection threshold during the primal 2 seconds. It suggests all the sensors are free from fault; in the next 4 seconds, only the fault indicator signal without N_c sensor informa-

Fig. 2 N_c sensor fault at cruise conditionFig. 3 p_{43} sensor fault at cruise conditionFig. 4 N_c sensor fault at maximum thrust condition

tion does not change, the other fault indicator signals slightly increase but do not exceed the fault detection threshold. It suggests the N_c sensor is disturbed by some signals, but all the sensors are free from fault at this time; from 6 to 10 seconds, only the fault indicator signal without

Fig. 5 p_{43} sensor fault at maximum thrust condition

N_c sensor information does not exceed the fault detection threshold, the other fault indicator signals increase and exceed the fault detection threshold, then generate alarm. It suggests N_c sensor might be in faulty. Define $\Delta y_{\text{fault}} = 0.005$, calculate the fault isolation threshold by Eq. (14) based on the N_c sensor noise standard deviation shown in the table 1, $\lambda_{s2} = 35.65$; after 10 seconds, only the fault indicator signal without N_c sensor information does not exceed the fault detection threshold, the other fault indicator signals exceed the fault isolation threshold. It suggests the N_c sensor fault; similarly, the other sensor fault in the other three modes can also be diagnosed by the double-threshold mechanism.

The fault occurred on different sensors are shown in Figs. 2 and 3. If fault isolation threshold is singly taken as a diagnostic threshold shown in Fig. 2, the mistake of the p_{43} sensor disturbance will occur; similarly, If fault isolation threshold is singly taken as a diagnostic threshold shown in Fig. 3, it will result in missed diagnosis of N_c sensor fault;

The same sensor fault occurred in different conditions are shown in Figs. 3 and 5. If fault isolation threshold is singly taken as a diagnostic threshold shown in Fig. 3, it will result in missed diagnosis of p_{43} sensor fault in the maximum thrust condition; similarly, If fault isolation threshold is singly taken as a diagnostic threshold shown in Fig. 5, it will result in mistaking the p_{43} sensor disturbance for a fault in en-

gine cruise condition.

According to the double-threshold mechanism proposed, the fault diagnostic threshold changes with the sensor type and the engine condition. It greatly improves the accuracy and robustness of sensor fault diagnosis.

3.2 Simulation of aircraft engine component and sensor fault diagnosis

Set the T_3 sensor 2% bias fault, fan efficiency 2% and 6% degradation fault, fan efficiency 2% degradation and T_3 sensor 2% bias simultaneous fault. The fan efficiency 6% degradation fault is considered as serious component fault. To avoid repetition, representative sensor fault indication signals are selected (the $W_{ssr,i}$ without T_3 and N_f sensor information). The simulation results are shown in Figs. 6 to 12.

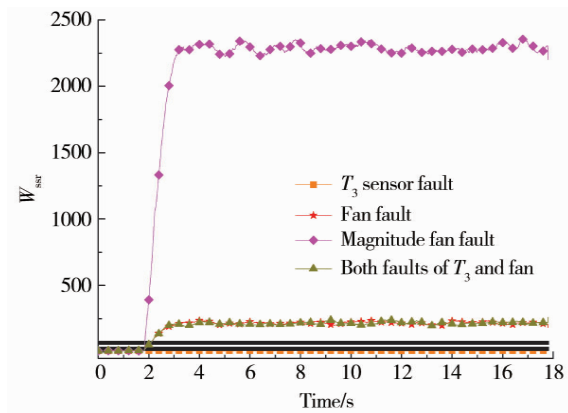


Fig. 6 Fault indication variable without T_3 sensor information under four kinds of faults

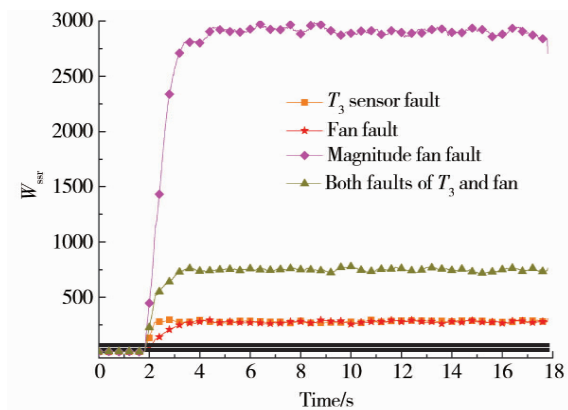


Fig. 7 Fault indication variable without N_f sensor information under four kinds of faults

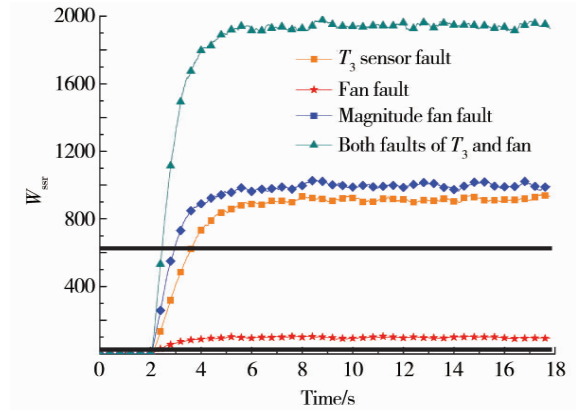


Fig. 8 Component fault indication variable under four kinds of faults

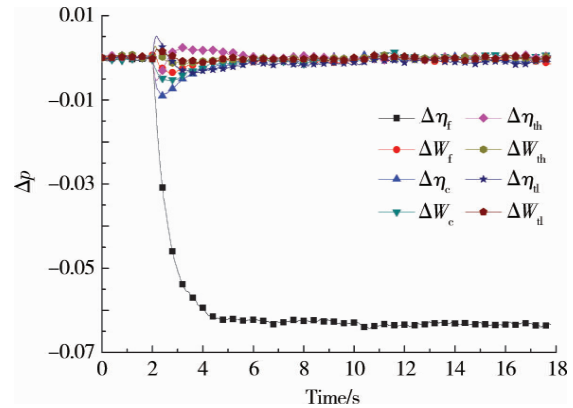


Fig. 9 Health parameters estimation under serious component fault

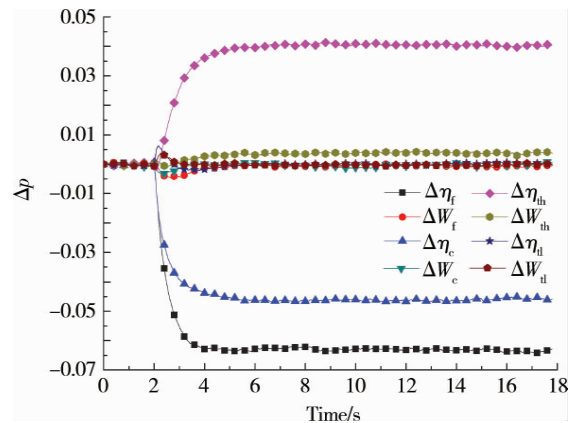


Fig. 10 Health parameters estimation under component and sensor simultaneous fault

According to the fault type detection mechanism: if the T_3 sensor is in faulty, the $W_{ssr,i}$ without T_3 sensor information does not exceed the fault detection threshold (shown in Fig. 6), while the others exceed the fault isolation

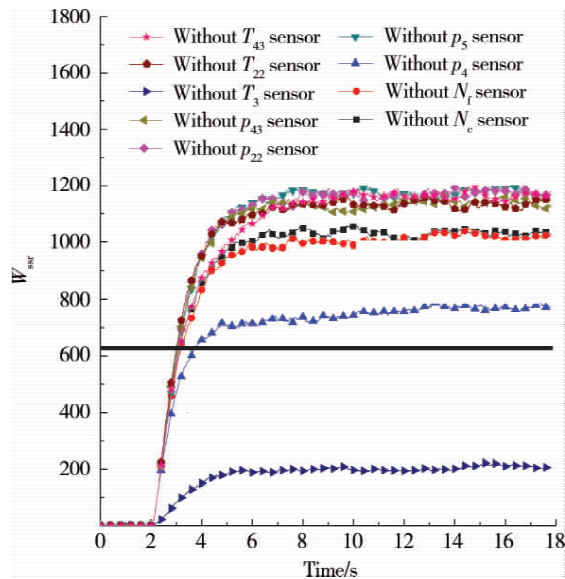


Fig. 11 Component fault indication variable without the removed sensor

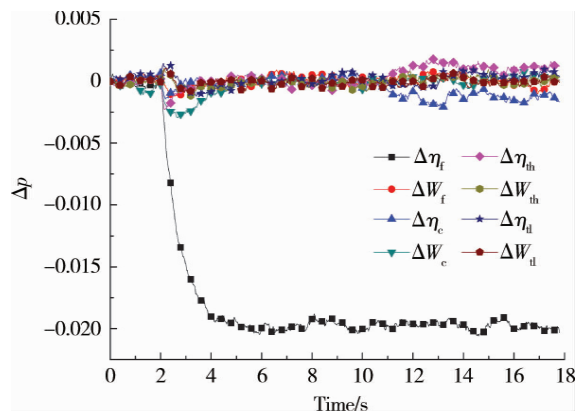


Fig. 12 Health parameters estimation without fault sensor

threshold as the $W_{ssr,i}$ without N_f sensor information (shown in Fig. 7), and the engine component fault indicators signal W_{ssp} exceed the second layer threshold (shown in Fig. 8); If the fan is fault, all the sensors fault indicators signals $W_{ssr,i}$ exceed the isolation threshold, while the component fault indicator signal W_{ssp} does not exceed the second layer threshold (shown in Figs. 6 to 8); if the component is seriously fault or component-sensor simultaneous fault, all the sensor fault indicator signal $W_{ssr,i}$ exceed the isolation threshold, and the component fault indicator signal W_{ssp} will also exceed the second layer threshold (shown in Figs. 6 to 8). We can judge that it's the component serious fault happens or component-sensor simultaneous fault happens

through the Figs. 9 and 10; if it is component-sensor simultaneous fault, the simulation results are given in Fig. 11. It suggests that the T_3 sensor is fault. The healthy parameters are estimated by the leaving 8 groups' sensors information. The simulation results are given in Fig. 12. It suggests the fan efficiency degenerate 2% fault. At last, we judged that the engine faults include T_3 sensor fault and fan efficiency degenerate 2% fault.

4 Conclusions

1) Aircraft engine component and sensor fault detection and isolation approach is proposed in this paper. It can not only distinguish among sensor fault, component fault and component-sensor simultaneous fault, but also isolate the fault sensor and locate the type of engine component fault when the engine component fault and the sensor faults occur simultaneously. The approach effectively improves the aircraft engine fault diagnosis ability.

2) The double-threshold mechanism is proposed in this paper. The fault threshold is determined by the sensor type and the engine condition, greatly improves the accuracy and robustness of sensor fault diagnosis system.

References:

- [1] Link C. Recent advancements in aircraft engine health management (EHM) technologies and recommendations for the next step[R]. 50th ASME international Gas Turbine & Aero engine Technical Congress, GT2005-68625, 2005.
- [2] JIANG Caihong, SUN Zhiyan, WANG Xi. Critical technologies for aero engine prognostics and health management systems development[J]. Journal of Aerospace Power, 2009, 24(11): 2859-2594. (in Chinese)
- [3] XUE Wei, GUO Yingqing. Aircraft engine sensor fault diagnosis based on estimation of engine's health degradation[J]. Chinese Journal of Aeronautics, 2009, 22(1): 18-21. (in Chinese)
- [4] Simon D L, Garg S. A systematic approach to sensor selection for aircraft engine health estimation [R]. NASA/TM-2009-215839, 2009.
- [5] Simon D, Simon D L. Aircraft turbofan engine health estimation using constrained Kalman filtering[R]. NASA/TM-2003-21252, 2003.

- [6] Dewallef P, Leonard O. On-line performance monitoring and engine diagnostic using robust Kalman filtering techniques[R]. ASME Turbo. Expo. ,GT2003-38379,2003.
- [7] Borguet S,Dewallef P,Leonard O. On-line transient engine diagnostics in a Kalman filtering framework[R]. ASME Turbo. Expo. ,GT2005-68013,2005.
- [8] Merrill W C,DeLaat J C,Bruton W M. Advanced detection, isolation, and accommodation of sensor failures real-time evaluation[J]. Journal of Guidance, Control and Dynamics, 1988, 6(11): 517-526.
- [9] Kobayashi T, Simon D L. Application of a bank of Kalman filters for aircraft engine fault diagnostics [R]. ASME Paper GT2003-38550, 2003.
- [10] LU Feng, HUANG Jinqun, CHENG Yu. Research on performance fault fusion diagnosis of aero-engine component[J]. Journal of Aerospace Power, 2009, 24(7): 1649-1653. (in Chinese)
- [11] Kobayashi T, Simon D L. Evaluation of an enhanced bank of Kalman filters for in-flight aircraft engine sensor fault diagnostics[J]. Journal of Engineering for Gas Turbines and Power, 2005, 127(3): 497-504.
- [12] DOU Jianping, HUANG Jinqun, ZHOU Wenxiang. Research of aeroengine modeling based on UML[J]. Journal of Aerospace Power, 2005, 8(4): 684-688. (in Chinese)