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Multi-Indicator Fusion Strategy for Health Monitoring of Engine Starting System

Gui-Qiang XU [a,1] , Shu LI [a] , Zhen-Yi ZHU[a] , Zi-Jian HUANG[b]
[a] *COMAC Software Co., Ltd., Chengdu, 610000, P.R. China*
[b] *School of Reliability and Systems Engineering, Beihang University, Beijing, 100191, P.R, China*
ORCiD ID: Gui-Qiang XU: https://orcid.org/0009-0000-3473-9004

Abstract. To effectively monitor the performance status and early warning of engine starting system, the multi-indicator fusion strategy for health monitoring of engine starting system is proposed by comprehensively considering the starting valve and starter performances. Combined with the operation principle of starting valve and starter in the starting system, the quick access recorder (QAR) parameters that can reflect the performance change of starting process are selected; the pressure value at the entrance of the starter is obtained by using the auxiliary power units (APU) pressure attenuation coefficient, and then the work energy is determined by integrating the starting process pressure; the operating time of the valve is calculated by the starting valve air volume-time curve, and the health indicator threshold of the valve and starter is obtained by using the regression fitting method and three-parameter Burr distribution, to realize the health state monitoring of the engine starting system. The results show that the accuracy of proposed method for engine health status monitoring can reach 90%, which can effectively reflect the performance changes of engine starting system, and can provide a reference for engine health management and predictive maintenance formulation strategies.

Keywords. multi-indicator fusion strategy, engine starting system, health monitoring, regression fitting method

1. Introduction

Aeroengine is one of the aircraft most critical components, and has long been a core part of researching aircraft health management. As the core part of the engine, the starting process of starting system is the key indicator to evaluate the engine performance[1]. Due to the high cost of the aviation engine starting system spare parts, there is often a lack of spare parts in the outfield base. Once the starting system appears failures such as hot start and start-up suspension, the aircraft may enter the AOG state, and the safe and stable operation of the aircraft can not be guaranteed, resulting in losses to the operator[2]. Therefore, the predictive maintenance of engine starting systems is of great significance to aircraft operators. However, there is a lack of research on health state monitoring modeling of the aeroengine starting system due to the complex structure, numerous parameters, and a large amount of data.

At present, the aeroengine health monitoring methods are mainly divided into two categories: the evaluation method based on system mechanism model and the evaluation

[1] Corresponding Author: Gui-Qiang Xu, email: guiqiang070914@163.com

method based on data-driven[3-5]. The former is to establish a mathematical and physical model by analyzing the working principle and operating characteristics of complex hybrid; this method has strong interpretability and can accurately describe the system working mechanism.

The second method requires collecting historical operating data of the engine and describing nonlinear relationships based on machine learning methods, which can effectively describe the nonlinear relationship between engine data characteristics and health status monitoring. However, the above methods have high requirements for data volume and quality, and the complexity of the established model is high, resulting in poor interpretability. Researchers usually carry out engine health monitoring research based on a data-driven approach[6-8]. Bai et al. used the wavelet packet decomposition algorithm to analyze the vibration signal of diesel engine cylinder heads, constructed a multidimensional health evaluation indicator vector, and established a health evaluation model using convolutional neural network to achieve state evaluation[9]. Zhao et al. applied the data statistical fitting to get the engine baseline model for the engine state monitor[10]. Chao et al. established the fault monitoring and diagnosis model by the physical performance model combined with a deep learning algorithm, and the calculation result is better than the pure data-driven algorithm, to achieve more accurate fault diagnosis. Wu et al. accomplished the turbulence model through the three-dimensional simulation of the engine nozzle flow rate to realize the performance changes of engine bearing nozzle.

To solve the difficult quantification problem of the relationship between system parameters and health status, it is necessary to analyze the mechanism and performance changes of the system in operation, and then fully explore the changing relationship between multiple sensor data information and conduct statistical analysis. The study first models the performance changes of the starting valve and starter of the starting system based on the system operating mechanism, establishes the mechanism model, and determines the health indicators. Furthermore, the collected parameter data is used to interpret and describe the model, and big data analysis techniques are employed to statistically analyze engine starting data from the past five years to determine the threshold values for valves and starters, which are the warning lines for health indicators. This enables performance monitoring of the engine starting system. Finally, the actual operational data of a certain airline company is used for verification to achieve health status assessment.

The remaining sections of this paper are arranged as follows: the principle and parameter analysis of starting system are introduced in section 2. In section 3, the algorithm procedure and theoretical description are described. The case analysis and verification is performed in section 4. Section 5 provides a brief summary of the research work.

2. Principle and Parameter Analysis of Starting System

The object of this study is the starting system of a mainstream engine used by most airlines at present, whose function is to accelerate the engine from the static state to the working state of the slow car, and to convert the air pressure power into the engine high-pressure rotor speed N2 to ensure the normal operation of the engine; it is mainly used for engine ground start, air restart and engine cold rotation. The starting system is complex, and more than ten subsystems will participate in the whole starting process, including the control system (ECU), ignition system, fuel system, and auxiliary power unit (APU).

2.1. Composition of Starting System

The starting system includes APU, starting valve (SAV), air intake pipe, air starter (ATS), electronic control assembly (ECU), and engine starting switch. The pressure potential energy is converted into kinetic energy by using the air turbine in the compressed air impact starter to do work, thus driving the high-pressure compressor of the engine to rotate. The air that drives the starter comes from the APU or other already started engine or ground air source. The scenario of this study is that the engine starts on the ground and uses APU for air supply. The engine starting procedures usually consist of a normal starting procedure (automatic) and a standby starting program (manual).

2.2. Working Principle of Engine Starting

When the engine starts normally or turns cold on the ground, the starting switch in the driving cabin is set to GND bit, and the start signal is transmitted to the starting control logic of engine control system ECU by the ARINC429 format. An open command is issued to SAV and the APU is entered into the starting mode. Afterwards, the power will be supplied to the SAV. When the electromagnetic valve in the SAV is powered on, it will change the state of the torsion spring, which in turn will cause the butterfly valve to the fully open position and supply the required air to the starter. Then N2 starts to rotate under the drive of the starter motor; When N2 reaches 22%, the ECU controls the fuel metering valve FMV to open and supply fuel to the combustion chamber. After 2-3 seconds, the starter and engine will simultaneously perform work at approximately 25%; When N2 reaches 50%, the ECU will control the start valve to close and control the clutch in the starter, automatically disengaging the rotating shaft of the AGB, and the starter will stop working, and only the engine does work; The starting switch automatically rebounds to the OFF position, ending the starting process, and the engine remains in idle mode autonomously.

2.3. QAR Parameter Determination

The ground automatic starting process is taken as the research object, the parameters reflecting the performance changes of the starting valve and the starter are selected.

According to the above analysis, the monitoring content mainly includes engine starting switch signal, starting valve unclosed signal, fuel metering valve signal, APU pressure, and high-pressure rotor speed. The parameters related to the starting process selected from QAR are listed in Table 1.

Table 1. QAR parameters related to the starting process

Serial number	Name	Mean
1	ENG_START	Engine start switch signal
2	SAV_NOT_CLS	Start valve not closed signal
3	FUEL_FLOW	Fuel flow
4	FMV_SEL	Rotation opening
5	N2	High pressure rotor speed
6	APU_BLD_PRESS	APU bleed air pressure
7	APU_P2_PRESS	APU inlet static pressure

3. Algorithm Procedure and Theoretical Description

3.1. Algorithm Procedure

Aiming at the research of engine starting system health monitoring, firstly, flight data are obtained by QAR decoding, and the monitoring parameters related to the performance of starting system are selected. The health indicator is determined by the analysis of the system structure and mechanism, and performance modeling of starting valve and starter motor. Besides, the testing data is applied to verify the effectiveness of the proposed algorithm. The process of presented algorithm is shown in Fig. 1.

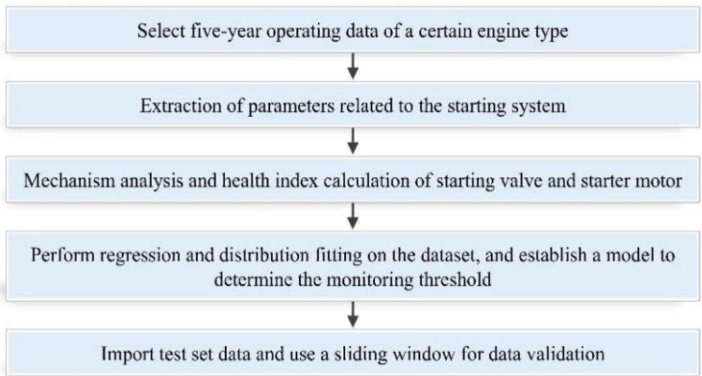

Figure 1. Process of presented algorithm.

3.2. Multi-indicator Fusion Strategy

Multi-indicator fusion strategy is employed to evaluate the health status of the starting system, which contains starting valve and starter performance indicators.

3.2.1 Starting valve performance indicators

The opening/closing instruction signal of the starting valve comes from the starting switch. The opening/closing status and position information of the starting valve can not be directly monitored, because there is no data about the starting valve position and opening in the QAR data. Then the performance change of the valve is analyzed indirectly by analyzing the starting valve output flow.

The performance monitoring is carried out by analyzing the corresponding relation curve between valve operation time and airflow volume (abbreviated as the volume-time curve of entrained gas). Based on the starting valve action time, the output air volume Q of the butterfly valve is calculated, which can be written as

$$Q = VS \times T \tag{1}$$

where S is the cross-sectional area of the air-entraining pipe; V represents the air-entraining velocity; S does not change during the working process, and V remains the same under the same external environment, so S and V are regarded as constants.

In this paper, based on the relevant maintenance technical data, the time from SAV_NOT_CLS=YES to N2 > 0 is taken as the action time T of the starting valve. Because the airflow Q at which the starter drives the high-pressure rotor to start rotating during each start-up process is approximately the same, the shorter the time, the faster the engine starts rotating. T can indirectly reflect changes in the volume of airflow in the pipeline, thereby reflecting changes in SAV performance. Therefore, the shorter the time between the opening of SAV and beginning of N2 rotation is enough to directly reflect the performance of SAV, and the operating time T is used as a health indicator to reflect the starting valve performance.

3.2.2 APU Error Analysis

The efficiency of the starter determines the amount of work done. To quantify the amount of work done during each starting process, it is necessary to integrate the pressure at the inlet of the starter motor. Then the trend of starter and APU pressure changes are analyzed because the error between starter and APU pressure value in QAR. According to the recorded air pressure parameters PU_BLD_PRESS at the APU outlet and APU inlet static pressure P2 in the aircraft, the air pressure at the APU outlet can be obtained by measuring the total air pressure of the load compressor (PBLD) and the static pressure at the APU inlet (P2), i.e., the APU gauge pressure value can be expressed as

$$P_{apu} = P_{BLD} - P_2 \tag{2}$$

Within the starting system, the APU outlet pressure and ATSV inlet pressure can cause obvious errors due to the environment and system structure; refer to the Honeywell APU pressure calculation manual, the errors at different heights are illustrated in Table 2.

Table 2. APU pressure varies with altitude.

Altitude (ALT)	APU outlet pressure (P_{apu})	ATS inlet bleed pressure （P_{ats}）	Pressure error between APU and ATS (D)
0ft	45.1psig	38.8 psig	6.3 psig
15000ft	29.6psig	25.5 psig	4.1 psig

By calculating the relationship between the pressure error D and the outlet pressure of APU, it is found that the efficiency attenuation varies linearly, and the attenuation coefficient k of APU pressure is calculated to be equal to 0.138, so the pressure at the entrance of ATS/SAV at different air pressure height can be obtained.

$$P_{ats} = (1-k)P_{apu} = 0.862(P_{BLD} - P_2) \tag{3}$$

Since the engine begins to provide power at 25% of N2, this paper only studies the situation where work is done only by the starter before 25%. The energy change of the whole process is that the potential energy of the air intake pressure after the starter is converted into the high-pressure rotor N2 kinetic energy (i.e., the engine kinetic energy Weng). The friction can form resistance in the process of motion because the starter is physically connected to the high-pressure rotor. The energy Wdrag consumed by resistance in the starting process of the same series engines is fixed, which can be expressed as

$$W_{eng} = W_{ats} - W_{drag} \tag{4}$$

The starter converts the pressure generated by the APU into kinetic energy that drives the high-pressure rotor to rotate, causing the engine rotor speed N2 to run to 25%. Therefore, the work done by the starter during each starting process can be calculated based on the pressure integration method, i.e.,

$$W_{ats} = \int_{t_1}^{t_2} P_{ats}(t)dt = \int_{t_1}^{t_2} 0.862 * (P_{BLD}(t) - P_2(t))dt \tag{5}$$

where t1 is the time when N2 starts to rotate; t1 denotes the time when N2 rotates to 25%; Pats(t) is the intake pressure of ATS at t time; Wats represents the energy produced by the starter work done.

Normally, the bleed pressure is a constant value, and the high-pressure rotor speed N2 represents the energy produced by the engine at the moment. N2 is 25%, which means the engine energy is constant at this time, i.e. the Weng and Wdrag are constant. The starting performance of the starter is poor when Wats is larger. Therefore, Wats is used as a health indicator to monitor changes in starter performance.

4. Algorithm Procedure and Theoretical Description

Based on the operating mechanism and mathematical model of the starting system, different indicators are extracted from the starting valve and starter to reflect the performance changes of the components. The training and testing sets of SAV and ATS are established respectively by collecting 27000 flight data of an airline. Data mining techniques are used to calculate the set of indicators and fit the data. The monitoring threshold Ysav and Yats for health indicators is obtained based on expert experience. The indicator value of the test flight is compared with the monitoring threshold value to realize the system health monitoring.

4.1. Start Valve Data Analysis

The training set consists of 12000 sets of data, and the set of health indicators for SAV is calculated, which smooth spline curve are shown in Fig. 2.

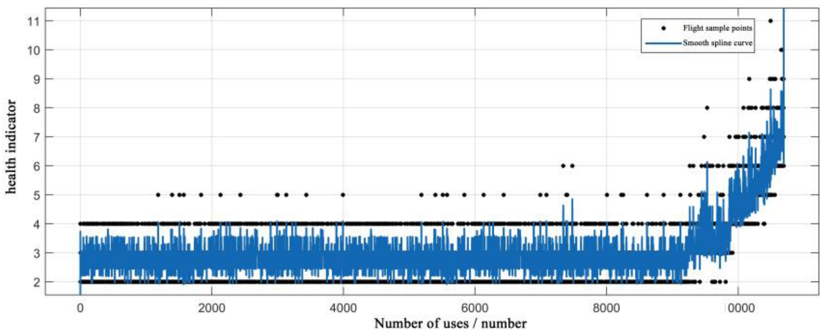

Figure 2. Smooth spline curve of SAV health indicators.

As described in Fig. 2, the health indicator T of the starting valve performance exhibits two forms of variation, i.e., stable operation in the first half and rapid performance degradation in the second half. In this case, the fast decay segment of SAV performance is fitted by regression, as illustrated in Fig. 3.

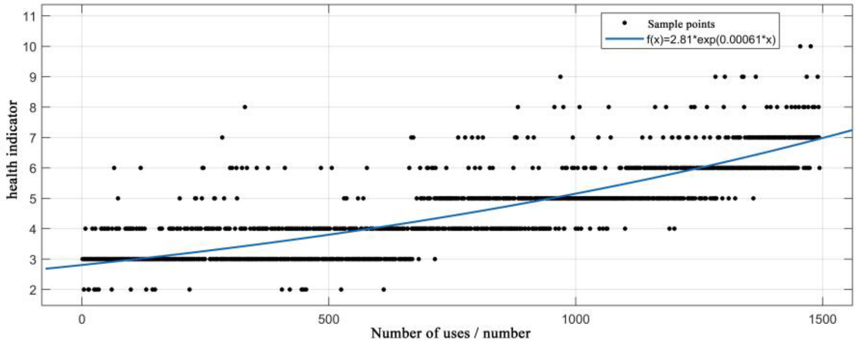

Figure 3. Smooth spline curve of SAV health indicators.

The regression equation for the performance degradation stage is expressed as

$$f(x) = 2.81 * \exp(0.00061 * x) \tag{6}$$

According to equation (19), the R2 and RMSE are 0.6841 and 0.7995. Based on the engine maintenance manual and expert experience, when T is greater than 6, it can be determined that the starting valve opens slowly and with a delay. Therefore, the monitoring threshold Ysav for T is set to 6.

4.2. Starter Data Analysis

Data fitting analysis. The fitting results of the three parameter Burr distribution function are shown in Fig. 4 and Fig. 5, respectively.

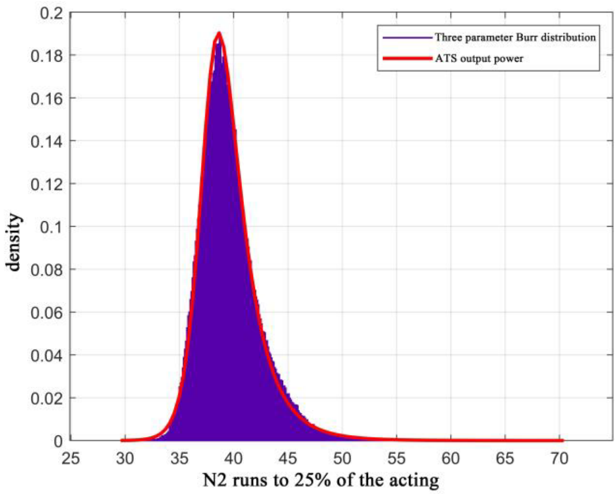

Figure 4. PDF curve of three parameter Burr distribution function.

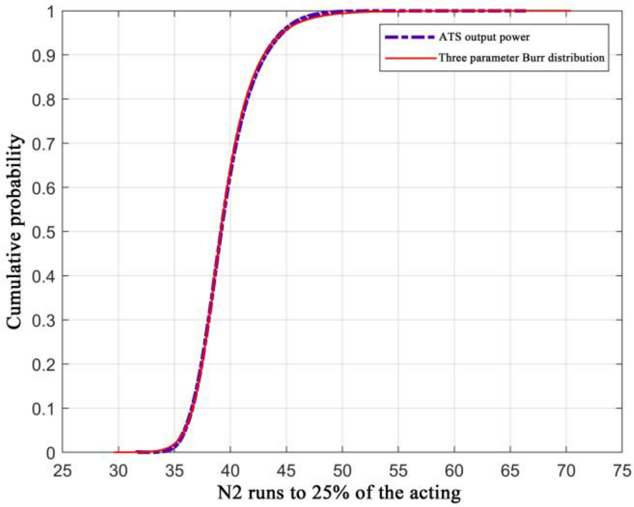

Figure 5. CDF curve of three parameter Burr distribution function.

From Fig. 4 and 5, it can be seen that the starter power data is similar to the probability density curve of the three parameter Burr distribution, and the peak positions are basically the same. The cumulative probability curve basically overlaps with its cumulative frequency curve.

Determination of monitoring threshold. To accurately screen starter motors with poor performance efficiency for precise maintenance, it is necessary to set a failure probability indicator q and calculate the monitoring threshold based on the PDF formula. In the field of civil aircraft safety, the unscheduled removals rate (URR) is commonly used as a fundamental parameter for system reliability, i.e.,

$$URR = (\alpha * 100) / (T * \beta) \tag{7}$$

where α represents the number of times system components have been disassembled and replaced; T is the total flight time of the fleet, and β is the number of aircraft installed for each system component.

Based on the replacement data of starter components from 100 aircraft of a certain airline for 375000 flight hours, the URR is calculated to be 0.01%, i.e., q=0.01%. The probability of meeting the starting criteria is 0.99%. Furthermore, the monitoring threshold is 48.7.

4.3. Testing Data Validation

To verify the effectiveness of the method proposed in this paper, the actuation time T of the starting valve and the work Wats of the starter are calculated separately based on 15000 sets. The window size is taken as j=3. Compare the results obtained from the start-up performance analysis model and the manual evaluation by maintenance engineers by treating the portion exceeding the threshold as abnormal data, as shown in Fig. 6 and Fig. 7.

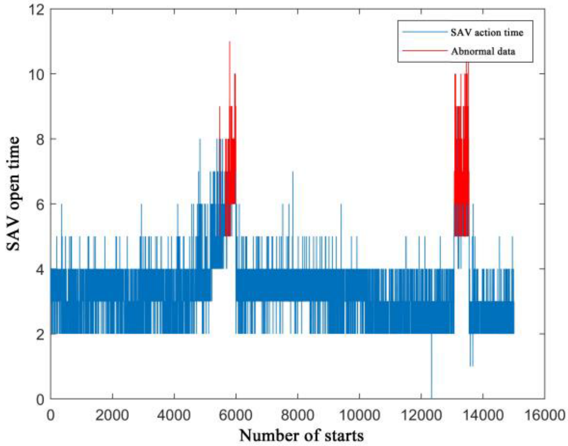

Figure 6. Simulation results of ATS sliding window abnormal data.

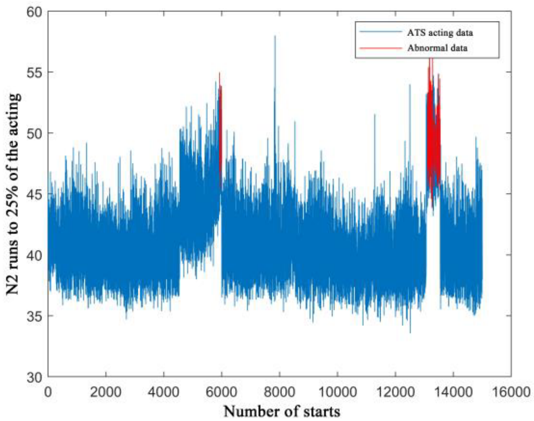

Figure 7. Simulation results of SAV sliding window abnormal data.

According to Fig. 6 and Fig. 7, the accuracy of ATS and SAV models is 90.6% and 89.7%, respectively.

The data indicators of the starting valve and starter before maintenance are accurately calculated through the above analysis. The proposed method has strong robustness and can better adapt to the jump data generated in the engine, and effectively identifying stages of rapid performance degradation. To determine whether the system needs predictive maintenance and achieve health monitoring of the engine system.

5. Conclusions

This article proposes a multi-indicator fusion health status monitoring method for engine starting system performance monitoring. The effectiveness of the proposed method is verified through actual operating data from a certain airline company over the past five years. The main conclusions are as follows:

(i) Based on the mechanism of the starting system, a multi-indicator fusion strategy for monitoring the health status of the starting system has been developed by integrating

APU pressure attenuation coefficient, bleed air volume time curve, regression fitting method, and three parameter Burr distribution;

(ii) The proposed method is validated using 27000 sets of flight data from a certain airline company, and the accuracy of engine health monitoring reached 90%;

(iii) The proposed method can quantify the performance degradation degree of the starting system, achieve predictive maintenance of the aircraft engine starting system, and reduce unplanned maintenance frequency. In addition, the explored methods have significant reference value for the health management research of aircraft engine starting systems, and also have important guiding significance for relevant enterprises in the industry to carry out predictive maintenance of starting systems.

References

[1] Li X Z, Gao L. Study on the Influence of Starting Conditions on Turbofan Engine Starting at Plateau[J]. Engineering&test, 2022, 62(4): 72-74.

[2] Ren G, Wang Y, Shi Z, et al. Aero-Engine Remaining Useful Life Estimation Based on CAE-TCN Neural Networks[J]. Applied Sciences, 2022, 13(1): 17.

[3] Kim S, Im J H, Kim M, et al. Diagnostics using a physics-based engine model in aero gas turbine engine verification tests[J]. Aerospace Science and Technology, 2023, 133: 108102.

[4] Ma S, Wu Y F, Zheng H, et al. Aircraft engine fault diagnosis based on flight process data[J]. Journal of Propulsion Technology, 2023, 44(5): 280-291.

[5] Liu W M, Hu Z Z. An aeroengine remaining useful life prediction method based on neural network[J]. Aeroengine, 2021, 47 (3): 8-15.

[6] Wang X, Li Y, Xu Y, et al. Remaining useful life prediction for aero-engines using a time-enhanced multi-head self-attention model[J]. Aerospace, 2023, 10(1): 80.

[7] Chen C, Zheng Q, Zhang H. Research on selection method of aero-engine health parameters based on correlation and condition number[J]. Proceedings of the Institution of Mechanical Engineers, Part G: Journal of Aerospace Engineering, 2023, 237(13): 2939-2951.

[8] Xu J H, Wang X L, Qang Y, et al. Research on method and application of bow-tie analysis based on D-S evidence theory[J]. Fire control & command control, 2019, 44 (10): 1-7.

[9] Bai Y J, Jia X S, Liang Q H, et al. Evaluation of diesel engine valve health status based on deep learning[J]. Science technology and engineering, 2022, 22 (10): 3941-3950.

[10] Zhao J, Tang Y D. Research on civil aviation engine condition monitoring based on ACARS data[J]. Computer Simulation, 2020, 37(8): 49-52.