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Evaluation of Equipment Performance for Altitude Test Facility Flight Environment Simulation System

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Abstract. Based on the predictive maintenance requirements of aero-engine Altitude Test Facility (ATF) equipment, a test equipment performance evaluation method (PCA-SPR) combining principal component analysis (PCA) and statistical pattern recognition (SPR) is proposed. It uses the PCA method to reduce the dimensionality of the equipment features, and recognizes the equipment status based on SPR. Then it defines the equipment health indicators based on the sample similarity theory, and achieves the quantitative evaluation of the equipment status. This paper takes the special control valve of ATF as the research object. Based on the simulation platform of the ATF flight environment simulation system, the valve performance degradation mode is studied and the valve degradation simulation is performed. The proposed PCA-SPR algorithm is applied to the valve performance evaluation to verify the applicability of the algorithm.

Keywords: Altitude Test Facility, test equipment, performance evaluation, principal component analysis, statistical pattern recognition.

1. Introduction

The aero-engine Altitude Test Facility (ATF) is an indispensable tool for the development of advanced aero-engines and a strategic equipment for the development of aeroengine [1]. As an important part of the Altitude Test Facility, Altitude Test Facility flight environment simulation system occupies an important position in the entire high-altitude simulation test, and its equipment performance has an important impact on the altitude simulation test [2] In order to meet the test requirements of my country's new type of aviation power plants, it is urgent to carry out researches on the maintenance of test equipment for Altitude Test Facility flight environment simulation system and equipment performance evaluation.

Predictive Maintenance (PdM) is a kind of active maintenance management based on the status of the equipment, and timely maintenance of the equipment through the analysis of the status of the equipment [3,4]. Compared with preventive maintenance, this type of equipment state-based predictive maintenance strategy better combines the real-time operating status of the equipment. The timing of preventive maintenance no longer only depends on engineering tradition and maintenance experience. It takes into account the actual operating status of the equipment, and takes appropriate maintenance measures before the equipment has no abnormalities or failures to reduce the probability of equipment failure. At the same time, the quantitative analysis is introduced into the decision-making process, which further increases the scientific and reasonable decision-making [5]. Predictive maintenance has been extensively studied in the field of industrial equipment such as bearings [6], blades [7], and drive motors [8]. Applying the concept of predictive maintenance to Altitude Test Facility flight environment simulation system equipment maintenance and equipment performance evaluation is of great significance for improving the intelligence level of my country's test equipment.

Principal components analysis (PCA) is one of the most widely used data dimensionality reduction algorithms. It transforms high-dimensional features into low-dimensional features by reconstructing features, and has important applications in equipment performance evaluation [9]. Statistical Pattern Recognition (SPR) is a basic pattern recognition method. Statistical pattern recognition is a method of statistical

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classification of patterns, that is, the technique of pattern recognition combined with the Bayesian decision-making system of statistical probability theory, also known as the method of decision theory recognition [10]. By combining the PCA method with statistical pattern recognition, equipment performance evaluation can be achieved, and the current performance status of the equipment can be quantified, which can lay the foundation for subsequent equipment prediction and remaining life estimation [11]. This paper combines the PCA-SPR method and applies it to Altitude Test Facility flight environment simulation system equipment performance evaluation, quantifies the state of the Altitude Test Facility test equipment, and provides a basis for the predictive maintenance of Altitude Test Facility equipment in the future.

2. PCA-SPR-based Equipment Performance Evaluation Method

2.1. Principal Component Analysis

The feature vector of the device may have a high-dimensional nature, and some of the feature vectors are very related, resulting in duplication of information. Using PCA to perform feature dimensionality reduction on equipment features can reduce data redundancy, improve data utilization efficiency, simplify processing, and at the same time ensure the accuracy of the dimensionality reduction results.

Assume that the initial characteristic data set of the test equipment is:

$$X_i = \left[x_1, x_2, \cdots, x_{k-m}, x_{k-m+1}, \cdots, x_k, \cdots, x_i \right] \tag{1}$$

Normalize the initial feature vector, then perform projection transformation on the sample, and get the new coordinate system, abandon part of the coordinates based on the new coordinate system and reduce the dimension to, then the projection of the sample in the low-dimensional coordinate system can be obtained. Perform eigenvalue decomposition on the covariance matrix to obtain the eigenvalue:

$$\lambda = \left(\lambda_1, \lambda_2, \cdots, \lambda_{k-m}, \lambda_k, \cdots, \lambda_n \right) \tag{2}$$

Assuming that the reconstruction threshold μ, select the maximum value that satisfies the condition to sort the eigenvalues, then the eigenvectors related to the eigenvalues after dimensionality reduction can be obtained as

$$X_i^{'} = \left\{ x_1, x_2, \cdots, x_{k-m}, x_k, \cdots, x_{n^{'}} \right\} \tag{3}$$

2.2. Statistical Pattern Recognition

The equipment evaluation method based on statistical pattern recognition mainly includes two steps: equipment status recognition and equipment health assessment. Based on statistical pattern recognition, it can realize the status recognition of Altitude Test Facility test equipment, and determine the "good" and "bad" status of the test equipment; quantify the status of the test equipment based on the sample similarity theory, and realize the performance evaluation of the equipment status.

(1) *Equipment status recognition based on statistical pattern recognition*

Equipment state recognition is to use Bayesian decision rules to classify a given state pattern into the corresponding pattern class. The likelihood rate is defined as the standard for state classification. The derivation process of equipment state recognition is as follows.

Assume that the limited equipment status categories are:

$$\left\{ \omega_1, \omega_2, \ldots, \omega_C \right\} \tag{4}$$

The feature vector of the device state mode is:

$$\mathbf{X} = \left(x_1, x_2, \ldots, x_d \right)^T \tag{5}$$

Map the device data set to the device state category space $\Omega_i (i = 1, 2, \ldots, C)$ according to the decision rule. If the device data set is in, Ω_i then the device state is considered to belong to the category ω_i. If $p\left(\omega_j\right)$

represents the prior probability when a certain device state is in ω_j, $p\left(\mathbf{X}|\ \omega_j\right)$ represents the conditional probability density in state X. For the two device states ω_1 and, ω_2 ,if $\mathbf{X} \in \omega_1$,then

$$l_r(\mathbf{X}) = \frac{p\left(\mathbf{X}|\ \omega_1\right)}{p\left(\mathbf{X}|\ \omega_2\right)} > \frac{p\left(\omega_2\right)}{p\left(\omega_1\right)} \tag{6}$$

Among them, $l_r(\mathbf{X})$ is the likelihood rate, and this parameter is used as a criterion for selecting the device state. If the likelihood rate corresponding to an existing category is greater, it means that the current position state *X* can be considered as belonging to the category.

(2) *Equipment performance evaluation based on sample similarity theory*

After the equipment status is recognized, the equipment status category space is estimated based on the equipment status samples, and then the equipment status samples can be input for equipment health assessment. The concept of measuring the similarity between samples is used to quantify the performance of the equipment, and the health index (HI) of the equipment is defined to describe the performance of the equipment.

Assuming a multivariate Gaussian distribution:

$$\vec{X} \sim MVN(\vec{\mu}, K) \tag{7}$$

At the same time, the eigenvalues of multiple parameters after dimensionality reduction are obtained, and the weight ratio of the parameters can be calculated according to the eigenvalues. Assuming that the device's health parameter is 1 in the initial situation, the device health parameter index corresponding to the current device state sample can be defined as:

$$H(\vec{X}) = 1 - F_{\chi_p^2}\left(s \cdot \sum_{i=1}^{p} \lambda_i \tilde{x}_i^2\right) \tag{8}$$

In formula (8), λ_i is the eigenvalues of each parameter after dimensionality reduction; $\tilde{x}_i$ is standardized parameters; s is sensitivity multiplier; p is degrees of freedom after dimensionality reduction; H is the health indicator of the equipment. For the calculation of health indicators of multi-dimensional parameters, the weight ratio of the multi-dimensional parameters is obtained by calculating the characteristic values of the multi-dimensional parameters, and these dimensionality-reduced parameters are converted into health indicators according to the weight ratio and statistical law.

2.3. PCA-SPR-based Equipment Performance Evaluation Steps

Figure 1 shows the steps and process of the performance index prediction of test equipment based on PCA-SPR. The process mainly includes two parts. The first part is the dimensionality reduction of equipment parameters. By reducing the dimensionality of the data, the complexity of subsequent health index calculations is reduced, and at the same time, the parameters that have more important effects on each test equipment can be analyzed. The second part is the introduction of health indicators, and the calculation of the weight ratio of each parameter in combination with the characteristic values, and finally the practice sequence of equipment health indicators, which lays a data foundation for the subsequent prediction of the practice sequence based on the health indicators of the test equipment.

The specific steps for calculating specific health indicators are as follows:

①Through the analysis and equipment operation mechanism, the characteristic parameters related to equipment performance degradation are obtained, and this parameter is used as the input of the data set.

②Perform PCA dimensionality reduction processing on the data. First standardize the input data, then calculate the covariance matrix of the input data, calculate the eigenvalues of the covariance matrix, sort based on the eigenvalues, select a certain number of reduced-dimensional parameters according to certain threshold setting rules, and finally get the principal component after dimensionality reduction.

③Introduce the calculation formula of the equipment health index, and determine the weight ratio of the characteristic parameter according to the characteristic value of each parameter after dimensionality reduction. According to the weight ratio of each parameter, the final one-dimensional health index is obtained, and finally output the health index.

3. Altitude Test Facility Flight Environment Simulation System

3.1. Flight Environment Simulation System

The Altitude Test Facility flight environment simulation system establishes the engine's intake and exhaust environment conditions at different flight altitudes and Mach numbers by adjusting the engine intake pressure,

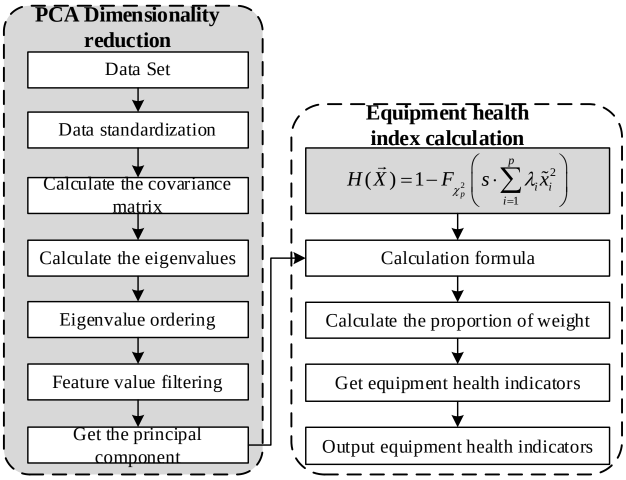


Fig. 1: PCA-SPR-based performance evaluation process

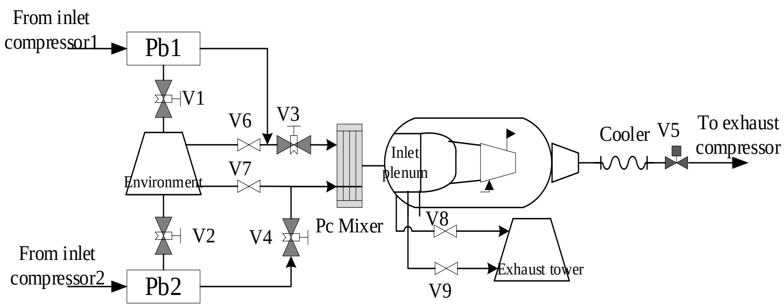


Fig. 2: Schematic diagram of ATF flight environment simulation system

temperature, and test chamber environmental pressure. The system consists of Pb1 system, Pb2 system, Pc system and Pd system, the schematic diagram of Altitude Test Facility flight environment simulation system is shown in Figure 2. The Altitude Test Facility flight environment simulation system establishes the engine's intake and exhaust environment conditions at different flight altitudes and Mach numbers by adjusting the engine intake pressure, temperature, and test chamber environmental pressure. The system consists of Pb1 system, Pb2 system, Pc system and Pd system, the schematic diagram of Altitude Test Facility flight environment simulation system is shown in Figure 2.

Pb1 system and Pb2 system are pressure control systems of pressure stabilizing chamber, which are controlled by V1 and V2 regulating valves; Pc system is the engine intake pressure and intake temperature control system, which is controlled by V3 and V4 regulating valves. V3 valve controls the intake pressure and V4 valve controls the intake temperature. Pd system is the engine exhaust environment pressure control system, which is controlled by V5 regulating valve. The engine exhaust pressure is established during altitude simulation test to simulate the flight altitude of aeroengine. V8 and V9 valves assist in regulating the altitude cabin pressure and temperature.

3.2. Flight Environment Simulation System Model

Figure 3 is the overall model of the Altitude Test Facility flight model simulation system simulation platform under MATLAB/Simulink.

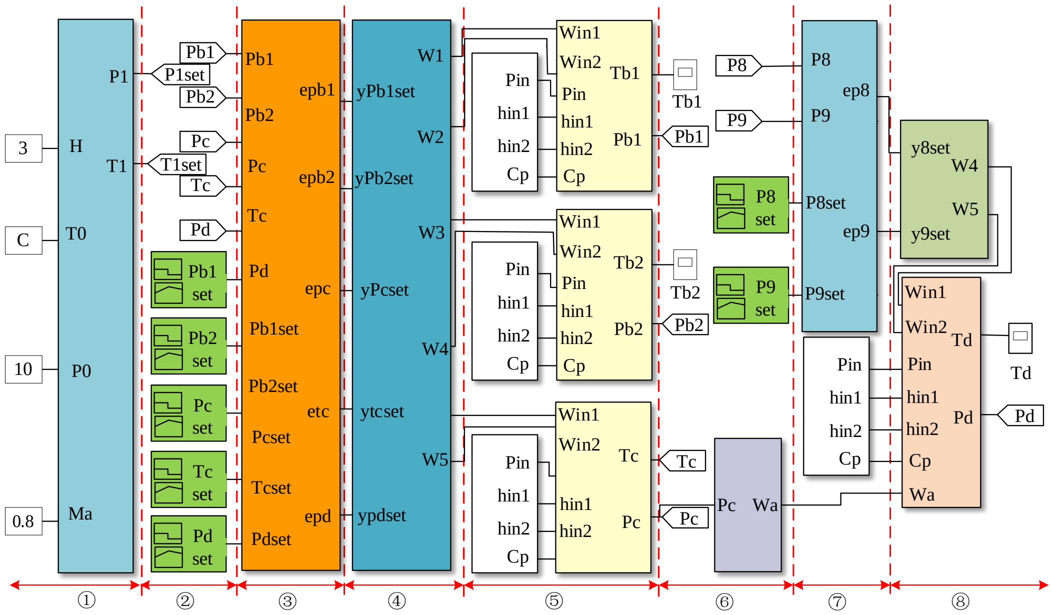
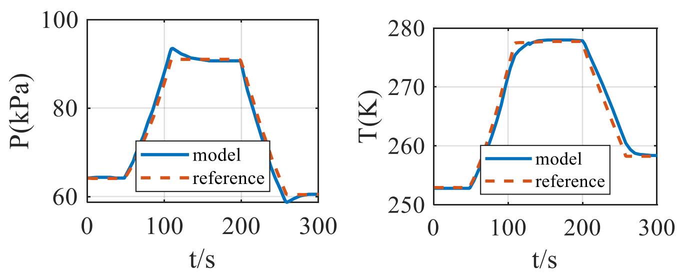


Fig. 3: Altitude Test Facility flight environment simulation system simulation platform

The whole platform can be divided into 8 parts; the part ① is the environmental condition calculation module; the part ② is the pressure and temperature setting module; the part ③is the module for generating intake and exhaust temperature and pressure control commands; the part ④ is the intake valve module, including five regulating valve flow models V1, V2, V3, V4, and V5; the part ⑤ is Pb1, Pb2, and Pc three pipe cavity model; the part ⑥ is the engine flow calculation model and the high-altitude cabin pressure setting module; the part ⑦ is the high-altitude cabin pressure control command generation module; the part ⑧ is the V8 and V9 two regulating valve flow models and Pd pipe cavity model.

In order to verify the control capability and flight test simulation capability of the flight environment simulation system, simulation tests are designed with real engine test projects (level flight acceleration test, equal Mach number climb test) to verify the versatility of the platform. The first is the level flight acceleration test phase: assuming that the engine is maintained at a flying altitude of 5km, the flying Mach number is uniformly accelerated from 0.5 to 0.9 within 1 min, and then the flying Mach number is kept unchanged at 0.9. Then proceed to the equal Mach number climb test stage: assuming that the engine's flying altitude climbs from 5km to 8km within 1min, and then keeps the altitude unchanged at 8km, the entire test simulation process lasts for 5min.

Combined with the schematic diagram of the Altitude Test Facility flight environment simulation system shown in Figure 2, a dual-channel PID controller is designed to control the intake temperature and pressure during the entire test process. Figure 4 is the temperature and pressure control effect diagram of the entire Altitude Test Facility flight environment simulation system.



(a) Intake pressure (b) intake temperature

Fig. 4:Intake pressure and intake temperature control effect

It can be seen from figure 4. that the flight environment simulation system can track changes in engine intake pressure and intake temperature to meet the needs of platform simulation and simulation.

4. PCA-SPR Algorithm Simulation Verification

The Altitude Test Facility flight environment simulation system contains numerous subsystems and test equipment. During the working process of the test equipment, due to vibration, shock, changes in cold and heat, aging and other factors, each test equipment is prone to various performance degradation and failures. This paper analyses and simulates the relevant parameters and typical failure modes of the Altitude Test Facility V3 control valve, simulates the performance degradation process of the valve, and lays a data foundation for the subsequent PCA-SPR-based valve state evaluation.

4.1. Analysis of Valve Performance Degradation Mode

Degradation of valve performance will affect valve characteristic parameters. By analyzing the changes in valve characteristic parameters, valve performance evaluation can be achieved. The characteristic parameters related to the V3 valve are shown in Table 1.

For Altitude Test Facility special control valve internal leakage and external leakage are the main decline situations, internal leakage can be simulated by increasing the flow coefficient to simulate this failure. The empirical formula for decay simulation of internal leakage is shown in equation (9).

$$K_v^f = \min\left(1, K_v^N (1 + 0.1 f)\right) \tag{9}$$

K_v^f is final flow coefficient; K_v^N is theoretical discharge coefficient; f is degradation intensity. The change trend of degradation intensity directly determines the predicted result. Engineering practice has proved that the exponential function has good performance in the characterization of degradation law.

Table 1: V3 valve characteristic parameters

Parameter name	Parameter label	Parameter name	Parameter label	Parameter name	Parameter label
Main valve position	V3	Vice valve position1	V31	Front pressure of valve	P1
Vice valve position 2	V32	Vice valve position 3	V33	Pressure after valve	P2
Mixer outlet pressure	Pm	Mixer outlet temperature	Tm		

The exponential regression function of the valve degradation intensity used in this paper is:

$$f = a_i \times \mathrm{e}^{b_i \times t} \tag{10}$$

a_i and b_i two coefficients of exponential fitting. Setting the simulation degradation intensity to 0, 0.1 and 0.15 respectively, establish the valve performance degradation model, inject the above two valve degradation modes into the simulation platform, set the simulation time to 5000s, and run the simulation platform during a certain engine test run to obtain the valve The degraded simulation result is shown in Figure 5.

The degradation factor f is changed according to the exponential degradation law of equation (10), and the simulated degradation factor is changed from 1 to 0.18, and 1000 sets of valve parameter data under different degradation conditions are obtained. Each set of valve data under degraded conditions includes 10 parameters under different degraded conditions in Table 1, and the number of simulation steps for each set of data is set to 5000, that is, each set of valve performance degradation contains data.

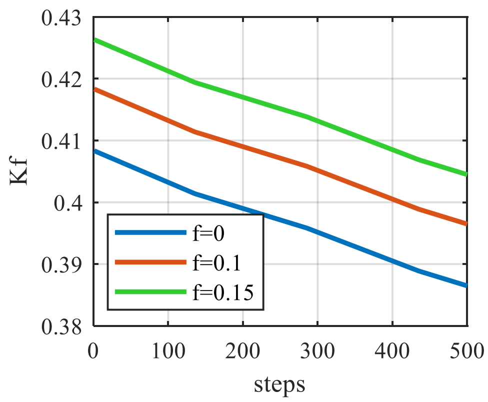


Fig. 5: Leakage simulation in V3 valve

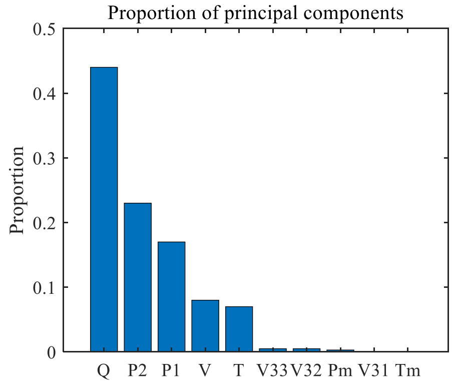


Fig. 6: V3 valve main component ratio

4.2. Valve Status Recognition Based on PCA-SPR

For the 10 characteristic parameters listed in TABLE 1, the PCA method is used to reduce the dimensionality of the 10 characteristic parameters. When the reconstruction threshold meets 95%, the dimensionality can be reduced to obtain 5 valve performance parameters. The sorting result of the principal component proportion of the V3 valve is shown in Figure 6. The parameter labels in Figure 6 are consistent with the parameter labels in TABLE 1, and finally the characteristic parameters of the V3 valve after dimensionality reduction are obtained:

$$X_i = \{V3、P2、P1、T、Q\} \tag{11}$$

Four sets of valve performance degradation data are selected, and the data contains 5 valve characteristic parameters after dimensionality reduction. Four sets of data are injected with different valve degradation factors through the model, and calculated by the method of statistical pattern recognition based on the main components of the valve obtained by screening. Likelihood rate, and then calculate the health index (*HI*) of these four kinds of degradation valve, the injected degradation factor and the calculated health index are shown in Table 2.

In Table 2, the degeneration factors of the first and the second group injected are similar, and the degeneration factors of the third and the fourth groups are similar. The health indicators of the first and the second groups calculated by the PCA-SPR method are similar, and the health indicators calculated by the third group and the fourth group are similar. At the same time, there is a certain correspondence between the health indicators of the two control groups and the degradation factors, and the results verify the correctness of the PCA-SPR method.

Table 2: Health indicators under different degradation factors

Group	Degradation factor *f*	Health indicators HI
First group	0.2	0.8134
Second Group	0.21	0.8029
Third group	0.5	0.5324
Fourth group	0.51	0.5217

5. Conclusion

Through this study, the following conclusions are obtained:

(1) Aiming at the performance evaluation of the Altitude Test Facility test equipment, a method based on the combination of principal component analysis and statistical pattern recognition (PCA-SPR) is proposed, and the characteristic control valve of the Altitude Test Facility is used as an example to verify. The results show that the method can realize the equipment Accurate evaluation of performance.

(2)Aiming at the Altitude Test Facility flight environment simulation system, a real engine test process was designed to verify the control effect of the flight environment simulation system; at the same time, the typical models of the Altitude Test Facility equipment performance degradation were analyzed and the equipment performance degradation simulation was carried out.

(3) According to the obtained equipment health indicators, the users can grasp the equipment performance status and understand the decline of the equipment, which can help construct the remaining maintenance life prediction model of the equipment, and help develop the equipment predictive maintenance strategy that is more in line with the actual situation and reduce the equipment. The cost of maintenance improves equipment safety.

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