International Journal of Business and Management Invention (IJBMI)
ISSN (Online): 2319-8028, ISSN (Print):2319-801X
www.ijbmi.org || Volume 10 Issue 1 Ser. III || January 2021 || PP 39-44

Research on fault diagnosis method of aero-engine sensor based on PCA

Xiaohu Lei
Corresponding Author: Xiaohu Lei.
School of Management, Shanghai University,

ABSTRACT: *In this paper, the application of PCA in fault diagnose of aero-engine sensor was investigated, and the specific algorithm was approved. Supposing only sensor fault was existed, the space of sensor measurements was divided into main measuring subspace and residual subspace. And then the fault diagnosis of the sensor fault was achieved with comparing the matrix in residual space projection of the practical measurement with normal data. The multivariate statistical characteristics figure was plotted with preceding the fault simulation platform for common faults of aero-engine sensors.Analysis of the simulation result shows that the method can detect effectively all kinds of aero-engine sensor faults.*

KEY WORD*: aero-engine; sensor; fault diagnosis; principal component analysis*

Date of Submission: 15-01-2021 Date of Acceptance: 31-01-2021

I. INTRODUCTION AND LITERATURE REVIEW

Areo-engine is the heart of the aircraft，its performance and reliability is an important guarantee of aircraft performance and flight safety. Real-time monitoring of the performance of aeronautical engines relies on sensors. Due to the complex structure of aero engine, aero engine sensors are usually in high temperature, high pressure and other harsh and complex working environment, sensor failure is frequent, accounting for a large proportion of engine control system failure. Therefore, it is of great significance to study the sensor fault detection technology and improve the level of fault detection to ensure flight safety.

In the fault diagnosis method of aviation engine sensor, the main meta-analysis method based on data is widely used. The fault diagnosis of the primary meta-analysis method is to use the correlation between multiple variables of the process to make the fault diagnosis. The main meta-model is established from the historical data of the variable, the degree of deviate of the new data sample from the main meta-model is tested, and the fault diagnosis is realized. For aeronautical engines, although an accurate model can be obtained at some point, the engine performance degrade and the accuracy of the model deteriorates with the running time. In this way, the advantages of the main meta-analysis method are apparent, it does not depend on accurate mathematical models.

In the existing research, Berrios proposed the use of fuzzy model-based fault signal estimators combined with primary meta-analysis and Q inspection, which were also evaluated on gas turbines at the San Isidro combined cycle power plant in Chile (Berrios & Paredes, 2009). The test shows a detection sensitivity of 1.5% relative to the measured value and a false alarm index of less than 0.3%. Some primary meta-analysis (PKPCA) has been studied for sensor fault detection and isolation of aeronautical gas turbine engines (Navi & Mwskin, 2015). In order to achieve fault isolation, a partial KPCA using the concept of parity relationship is proposed to generate a set of residual signals. The simulation study shows that the proposed method can effectively detect and isolate the occurrence of sensor failure in industrial gas turbines. Alawi introduces the sensor fault identification method using variable recombination of dynamic system, and evaluates its function compared with the dynamic PCA method using mathematical reference problem (Alawi & Morris,2007). Meléndez Used the variance of the reconstruction error, selects the set of sensors in the PCA model for engine sensor troubleshooting, and only faulty sensors are considered in the study (Melendez & Ruiz, 2009). Harmouche and others successfully detected initial failures that the observer could not detect using the proposed guidelines (Harmouche & Delpha, 2014). In addition, it isolates faults. Shun's research has found that primary meta-analysis is powerful and robust in troubleshooting (Shun & Wen, 2014).

In summary, for aero engines, a sensor fault diagnosis method based on the main meta-analysis method is given, and a specific diagnostic example is given for the sensor typical.

II. THE FUNDAMENTALS OF PCA

Under normal operating conditions, a data set $Y \in R^{m*n}$ is collected, where m is the number of samples and n is the number of variables measured by the sensor. For aero-engines, different variables have different dimensions, which will lead to greater dispersion of the values of each variable, making the total variance controlled by the variable with larger variance, so it is necessary to standardize the variables, the sample data is standardized to produce:

$$\bar{X} = [X - I_m u^T] D_\sigma^{-1/2} \qquad (1)$$

Where I_m is the n-dimensional column vector where all elements are 1, $u = [u_1, u_2, \cdots, u_n]^T$ and $D_\sigma = diag(\sigma_1^2, \sigma_2^2, \cdots, \sigma_n^2)$ are the average vector and the variance matrix, respectively. For ease of inference, the standardized X is also recorded as $\bar{X}$. The co-variance matrix of X is calculated, $S = XX^T/(n-1)$ is the correlation coefficient matrix of X, and the n characteristic value of S is $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_n$, and the corresponding orthosecting feature vectori is $p_1, p_2, \cdots, p_n$, matrix X can be broken down into:

$$X = TP^T + \tilde{T}\tilde{P}^T = TP^T + E \qquad (2)$$

which,$T \in R^{m*k}$,$\tilde{T} \in R^{m*(n-k)}$,$\tilde{P} = [p_{k+1}, p_{k+2}, \cdots, p_n] \in R^{n*(n-k)}$ are the main meta-load matrix and the residual load matrix are the main meta-load matrix, respectively, and k is the primary meta-number. In this way, the original data space is decomposed into two orthosecting subspaces, the primary metaspace (PCS) and the residual subspace (RS). The measurement data is then projected into these two subspaces to determine whether the system has changed. In general, the PCS in-projection $\tilde{X}$ mainly contains the normal value of the measurement data, while the RS in-projection $\tilde{X}$ mainly measures noise. In the event of a failure, the RS in-projection $\tilde{X}$ will increase significantly, which is the basis for troubleshooting.

The selection of the number of primary k will directly affect the accuracy of the main meta-model and the results of troubleshooting, and if not selected properly, effective diagnostics may not be possible. If the number of main metas is too small, the variance projected in the residual space is more, so that the threshold of fault detection is too large, resulting in false reporting, if the number of main metas is too large, it will make the variance distributed in the residual space is too small, so that the fault has little effect on the residual space, resulting in method failure. The determination of the number of primary metas has the method of the contribution rate of the primary and the method based on the variance of the minimum reconstruction error (Dunia & Qin, 1998). In this paper, the main meta contribution rate method is selected to calculate the number of main metas, and the main meta contribution rate method is the criterion for selecting the main metas:

$$\frac{\sum_{k=1}^{i} \lambda_k}{\sum_{i=1}^{n} \lambda_i} \geq cl \qquad (3)$$

Among them, cl is the threshold contribution rate. and $cl \in [0,1]$. Since the contribution rate of the primary is generally large, cl can be set to 95%. The maximum number of primary dollars that meet the criteria is recorded as k_1. The average of all feature values of the correlation coefficient matrix is then calculated:

$$\bar{\lambda} = \frac{1}{n} \sum_{i=1}^{n} \lambda_i \qquad (4)$$

Select feature values that are greater than the mean feature value as the main feature values, and discard those that are less than the mean. The serial number that corresponds to the smallest primary feature value is k_2. the maximum value of the k_1, k_2 is the number k of the main meta.

III. DIAGNOSIS AND ISOLATION OF FAULTS

When the main meta-model is built, you can import detection samples and draw multivariable statistical control charts. The commonly used multivariable statistical control charts have square prediction error charts (Chiang & Russell, 2000), T^2 charts, contribution charts, etc. Because the square prediction error graph has a stronger detection ability than the T^2 charts, this paper uses the square prediction error graph to detect whether a fault has occurred. square prediction error SPE is:

$$SPE = \|\tilde{X}\|^2 = X^T(I - P * P^T)X \qquad (5)$$

When $SPE \leq \delta^2$, the sensor is working properly, and when $SPE \geq \delta^2$, the sensor is considered to be faulty. Which δ^2 is The confidence limit of the SPE.

$$\delta_a^2 = \theta_1 \left[\frac{c_a \sqrt{2\theta^2 h_0^2}}{\theta_1} + 1 + \frac{\theta_2 h_0 (h_0 - 1)}{\theta_1^2} \right] \qquad (6)$$

Which $h_0 = 1 - \frac{2\theta_1\theta_3}{3\theta_2}$, $\theta_1 = \sum_{i=k+1}^{n} \lambda_i$, $\theta_2 = \sum_{i=k+1}^{n} \lambda_i^2$, $\theta_3 = \sum_{i=k+1}^{n} \lambda_i^3$; In the equation, k is the number of main elements of the model, c_a is the critical value of normal distribution at the test level of a, and λ_i is the characteristic value of the co-variance matrix of standardized processed data.

When the value of SPE exceeds the limit, that is, after detecting the fault, it is necessary to isolate the fault and determine which sensor has failed. The SPE contribution graph method can achieve fault diagnosis, its practice is to draw the residuals of X variables to SPE contribution graph, it reflects the changes of each variable on the stability of the system statistical model, for SPE has a greater contribution to the variables are most likely to fail, thus achieving fault isolation.

IV. VARIABLE SELECTION BASED ON CORRELATION

The operation of an aero engine follows the internal laws of the power balance of the compressor and turbine, as well as the overall flow balance of the engine, which makes the sensor's measurement signal have a great deal of correlation. The correlation of variables provides redundant information for fault detection, and also provides a necessary theoretical basis for the main meta-analysis method to be applied to sensor fault detection in aeronautical engine control systems. However, not all engine control system sensor measurement variables have a strong correlation between variables, which requires statistical methods from a large number of data to calculate the correlation coefficients between variables. Any two variables x_i and y_i are coefficients between the two variables are defined as:

$$\rho(x_i, y_i) = \frac{cov(x_i, y_i)}{\sqrt{var(x_i)var(y_i)}} \quad (7)$$

The resulting steady-state data can be used to estimate the correlation coefficient matrix between variables, so as to determine which variables have a strong correlation. Group variables based on correlation coefficients to form related vector groups. Here is a set of related variables, all five of which have correlation coefficients greater than 0.7. The relevant variable values are: low-voltage roulut speed XNLC, high-pressure roulut speed XNHC, low-voltage turbine infringing temperature T45, compressor outlet total pressure P31 and low-voltage turbine outlet total pressure P6.

V. THE FAULT DIAGNOSIS OF AREO-ENGINES SENSOR IS CARRIED OUT BASED ON PCA

The specific idea of fault diagnosis of aviation engine sensor by using the main meta-analysis method is to collect the sensor measurement data of a set of engines in normal working condition, to extract the statistical information of this set of data, to establish the main meta-model, to import the data samples to be tested, to draw the square prediction error map and the SPE contribution graph of various variables, and to carry out online fault detection.

5.1 PCA-based aero engine sensor fault diagnosis simulation analysis

The common types of faults of sensors are bias fault and drift fault. On the aero-engine fault diagnosis simulation platform, with a certain type of turbo fan engine at a steady-state conditions of height of H=2.5km, Mach number Ma=0.8, fuel flow WFM=3600kg/s, tail nozzle area $A_8 = 0.2984m^2$,, five important parameter sensors are selected, namely, low-voltage roulut speed XNLC, high-pressure roulut speed XNHC, low-pressure turbine infringing temperature T45, compressor outlet total pressure P31 and low-voltage turbine outlet total pressure P6.

(1) The establishment of the main meta-model: the main meta-analysis of a set of data in the stable running segment of the engine is carried out, and the main meta-model is established. This set of data consists of 200 sample data $X \in R^{200*5}$ and standardize the processing of the data. In this paper, the cumulative variance contribution rate is used to select the number of main metas. Since the cumulative contribution rate of the first two mains is 96.35%, which can explain more than 95% of the data changes, the number of selected mains is 3, and the SPE confidence limit is calculated: $\delta_a^2 = 4.22(a = 95\%)$.

(2) The sampling interval is 0.025s, the total sampling time is 10s, and at some points the low-voltage roel speed sensor is added to the fault signal.

(3) Import sample measurements to be tested, calculate SPE statistics using the newly established model, if the confidence limit is exceeded, indicate that the sensor has failed, and then isolate the faulty sensor through the SPE contribution diagram of each variable.

5.2 Sensor fault diagnosis and isolation

When no fault signal is added, the output curve of the low-pressure rotor speed sensor is shown in fig.1 ~ fig.2, when the SPE value does not exceed the confidence limit, indicating that the measured data of the sensor is normal.

Figure 1 XNLC sensor failure-free output

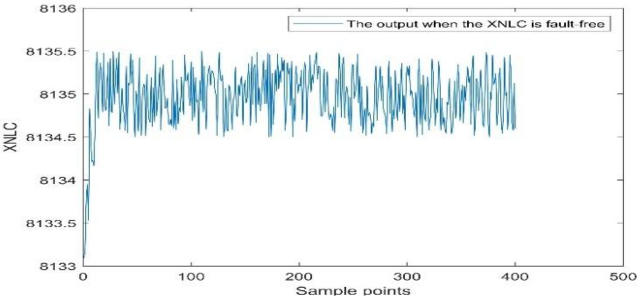


Figure 2 XNLC fault detection without fault

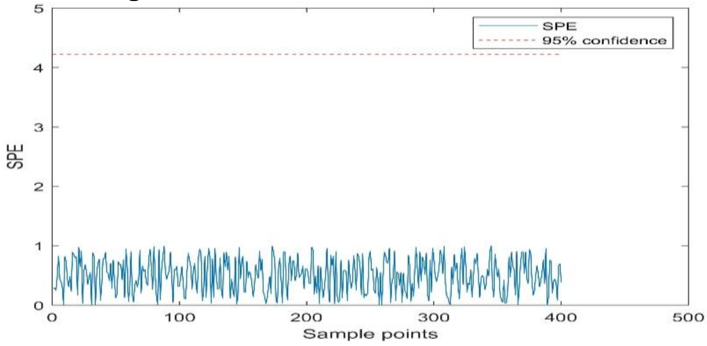


Fig.3 ~ Fig.5 is the result graph of offset fault diagnosis. At the 200th sampling time, a bias of 0.15% is added to the low-pressure rotor speed sensor. The fault data of XNLC is shown in Fig.3. Fig.4 is the result of the fault data detection. The SPE exceeds the confidence limit to detect the fault. Looking at the contribution graph of each variable (figure 5), the XNLC variable maintains a constant contribution to the SPE value from time 200, so it is judged that the XNLC sensor is most likely to fail.

Figure 3 Output of XNLC sensor in case of bias failure

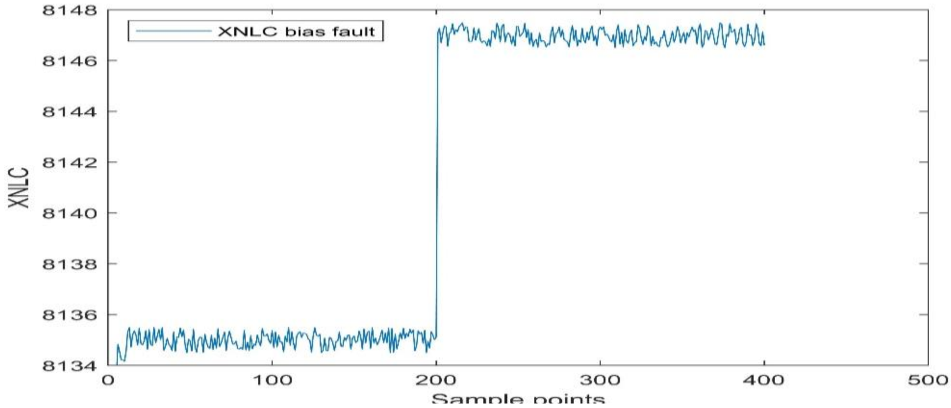


Figure 4 XNLC sensor bias fault detection

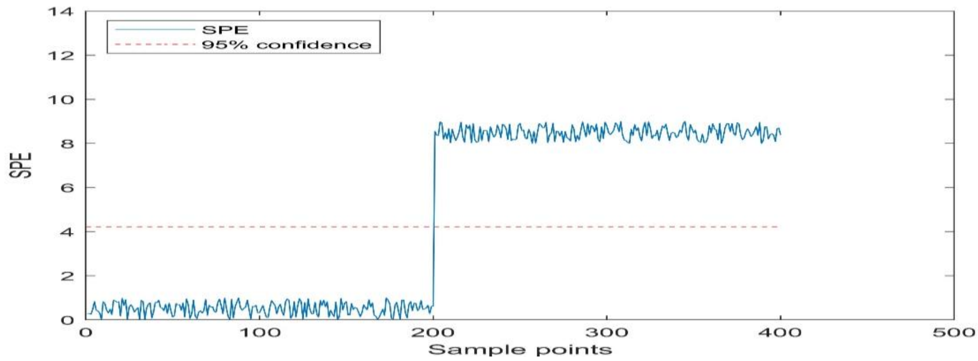


Figure 5 Fault isolation for bias failure of XNLC sensors

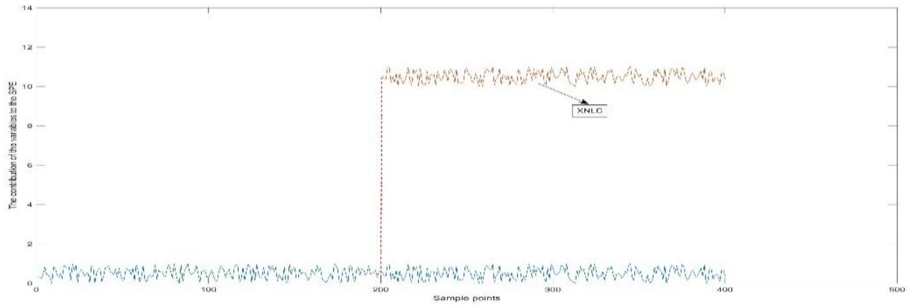


Fig. 6 ~ Fig. 8 is the result graph of drift fault diagnosis. At the 200th sampling time, a drift of 0.055% slope is added to the low-voltage rotor speed sensor. The fault data of XNLC is shown in Figure 6. Figure 7 is the result of fault data detection. At 200th time, the fault is very small, SPE value does not exceed the limit, can not detect the failure, with the passage of time, the degree of failure, SPE value is increasing, beyond the confidence limit, detected anomalies and failures. Looking at the contribution graph of each variable (figure 8), the XNLC variable has been increasing its contribution to the SPE value since 200, so it is judged that the XNLC sensor is most likely to fail.

Figure 6 Output of XNLC sensor in case of drift failure

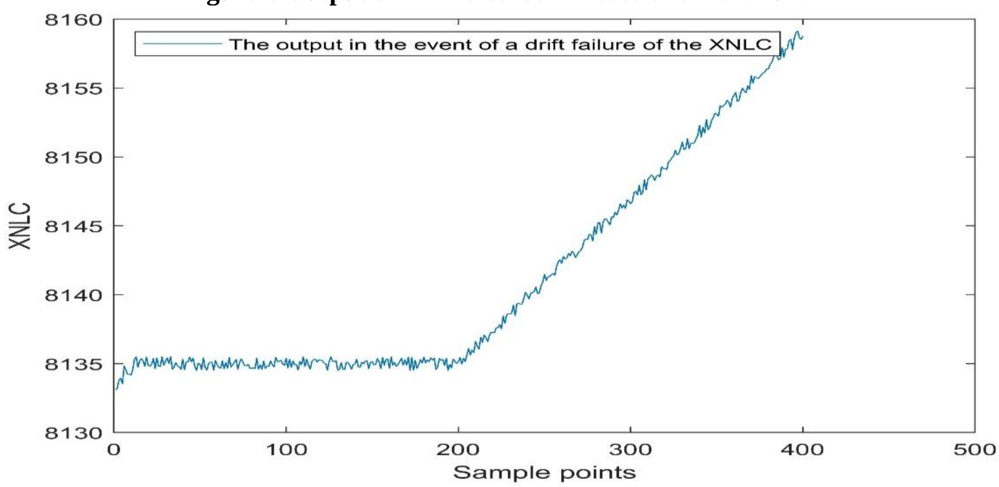


Figure 7 Fault detection of XNLC sensor with drift fault

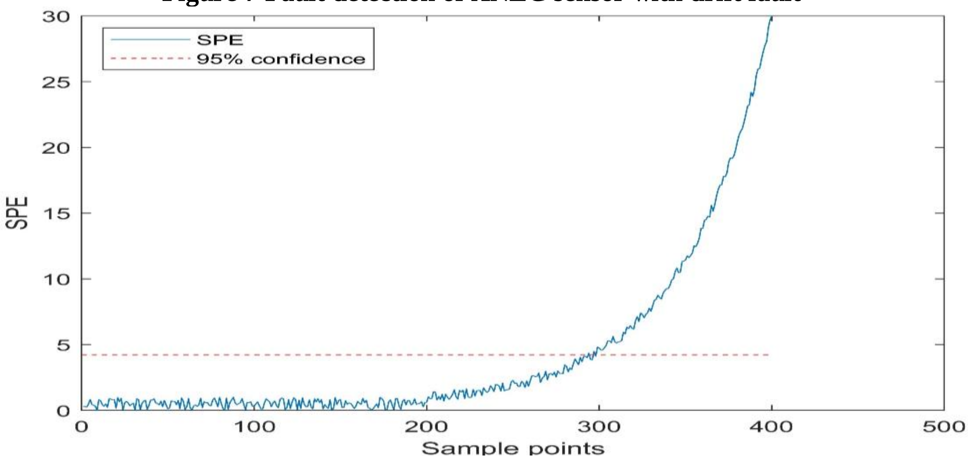
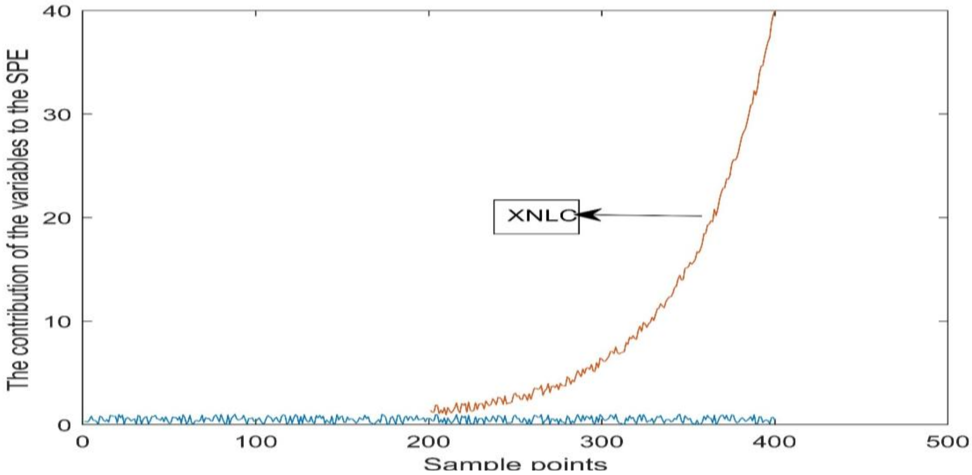


Figure 8 Fault isolation for XNLC sensor drift fault



VI. CONCLUSION

In this paper, based on principal component analysis (PCA) theory and common faults of aeroengine sensors, the fault diagnosis of aeroengine sensors in steady state is studied in Simulink environment of MATLAB software platform. The simulation results show that PCA can accurately detect two kinds of sensor faults, and it has good fault diagnosis ability for single sensor faults. However, this paper only studies the case of steady state, and how to extend to all states in the whole process needs further study and discussion in the future.

BIBLIOGRAPHY

[1]. Lee C, Sensor fault identification based on time-lagged PCA in dynamic process[J]. Chemometrics and Intelligent Labora-tory Systema, 2004(70): 165-178.

[2]. Berrios R, Paredes R, Cipriano A. Sensor fault detection and diagnosis in the gas turbine of San Isidro combined cycle power plant[J]. IFAC Proceedings Volumes, 2009, 42(8): 1354-1359.

[3]. Navi M, Meskin N, Davoodi M. Sensor fault detection and isolation of an industrial gas turbine using partial adaptive KPCA[J]. IFAC-PapersOnLine, 2015, 48(21): 1389-1396.

[4]. Alawi A, Morris J. Sensor fault diagnosis in dynamic processes[J]. IFAC Proceedings Volumes, 2007, 40(5): 267-272.

[5]. Melendez J, Ruiz M, Colomer J, et al. Statistical modeling for fault diagnosis of sensors of the ariane's engine[J]. IFAC Proceedings Volumes, 2009, 42(8): 1414-1419.

[6]. Harmouche J, Delpha C, Diallo D. Incipient fault detection and diagnosis based on Kullback–Leibler divergence using principal component analysis: Part I[J]. Signal Processing. 2014, 94： 278-287.

[7]. Shun L I, Wen J. A model-based fault detection and diagnostic methodology based on PCA method and wavelet transform[J]. Energy & Buildings, 2014, 68(1): 63-71.

[8]. Dunia R, Qin S J. Joint diagnosis of process and senor faults using principal component analysis [J]. Control Enginee ring Practice, 1998(6): 457-469.

[9]. Chiang L H A, Russell E L, Braatz R D. Fault detection and diagnosis in industrial systems [M]. London: Springer, 2000.

Xiaohu Lei. "Research on fault diagnosis method of aero-engine sensor based on PCA." *International Journal of Business and Management Invention (IJBMI)*, vol. 10(01), 2021, pp. 39-44. Journal DOI-10.35629/8028