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Recognition for Change-point of Aero-engine Components Based on Projective Transformation

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Abstract: With the development of Condition-Based Maintenance, there was a significant precondition for aero-engine to establish components faults recognition timely and accurately. The former studies mainly concentrated on components performance degradation but connections among engine working parameters and recognition of quantitative change of components faults were neglected. Based on change-point theory and SPSS statistical analysis, the key to quantitative change of components faults were analyzed through complanation of dualistic linear regressions. Finally, this method was calibrated and tested with the field data of turbojet engine life experiment to verify the validity and feasibility of this theory.

Key words: Turbojet engine, condition-based maintenance, projective transform, change-point recognition, statistical analysis

INTRODUCTION

Aero-engine components faults recognition was the important issue to ensure flight safety. Engine Monitoring System (EMS) (Hess and Fila, 2002) was a direct and effective way to monitor the working state of aero-engine. It was used for A-7E aircraft engine condition monitoring system in 1970s which provided supports for engine maintenance security with vibration sensors. Recently, Prognostics and Health Management (PHM) (Roemer *et al*., 2001) technology has developed to Condition-based Maintenance (CBM) (Guo *et al*., 2008). Although there were active effects for existing monitoring technology to ensure security and economy, the monitoring scope and depth were not enough. In addition, limited by mathematic models, The former research mainly concentrated on relationship between components parameters and performance (Fiorucci *et al*., 2000; Grapis *et al*., 2006; Dowson *et al*., 2004), but connections among engine working parameters and recognition of quantitative change of components state were neglected. When tip clearance was large enough to affect performance measurement, the faults could be detected. In leaf rubbing, only after wearing out enough materials with imbalance situation could vibration monitoring detect the fault, so vibration and performance monitoring was mainly used to indicate faults in late stage (Bhaumik *et al*., 2002; Hall and McMullen, 1992). Moreover, the borescopy, as off-line detection method, its real-time performance was not good (Li *et al*., 2007). The quantitative change is precondition and provision for qualitative change and there must be a qualitative change with the increase of quantitative change. The analysis of change point theory (Jingtian and Jiuen, 2000) was developed to study the quantitative changes of statistical theory recently. On a new aero-engine tests experiment, with advanced electrostatic induction monitoring technology (Li *et al*., 2009; Wen *et al*., 2010; Fu *et al*., 2013), regression change point model was set up by parameters of electrostatic induction signal, lubricating oil consumption, lubricating oil pressure. In order to improve detection efficiency and accuracy, projective transformation (Yu and Xiaoyuan, 2010) in descriptive geometry theory was proposed to simplify the change point model to one regression equation and it was identified and judged that the change point was existent when there was corresponding faults.

PRESENTATION OF CHANGE-POINT MODEL

Change point reflected the changes of inherent law as well as process from quantitative changes to qualitative ones. Generally, there were a series of observed values (samples), in most cases, these values

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arranged in chronological order, in a moment one do not know, the distribution of samples, or its statistical characteristics suddenly changed, so this moment was the change point. Linear regression analysis was a common method in change-point statistics, among them, one regression analysis which was studied with 2D scattered- plots to judge change-point visually, was the foundation for its more research and application. However, for binary regression model, it was difficult to make 3D scattered-points diagram and analyze space types intuitively. Accordingly, by projection transformation from three-dimensional plots, binary linear regression model was transformed into one regression change-point detection problems, from which the change point of source problem could be confirmed.

LINEAR REGRESSION MODEL ANALYSIS

Planarity principle of spatial problems:

- **Point projection and its characteristics:** As shown in Fig. 1a, for a space point A (x, y, z), three-projectional system was established (front projection V (XOZ), horizontal projection H (XOY), Lateral projection W (YOZ)), vertical lines from point A to the three projection were perpendicular to points a' (x, z), a (x, y), a'' (y, z). Then the horizontal projection plane H and lateral projection W were flattened to the same plane as frontal projection plane V, as in Fig. 1b. a' (x, z), a (x, y), a ''(y, z) were orthographic projections on the three basic projection plane projected from point A and they equipped with the characteristics of 'long for orthographic projection, height for parallel projection, width for equal projection'
- **Plane projection and its characteristics:** Generally, plane projection was still the similar type (plane); When plane was vertical to projection surface, the projection was accumulated as a straight line; If there was at least one line in plane being vertical to projection surface, so was the plane
- **Projection transformation:** By projection transformation, a common plane could be transformed into vertical projection plane. As shown in Fig. 1c, a new projection plane P1 was added in V-H system. Letting the projected-plane Δ ABC be perpendicular to P1 so that, Δ ABC was accumulated as a straight line in P1

Projection transformation of 3D scattered-points:

- **Binary regression model:** Binary regression equation was $y = a+b_1x_1+b_2x_2$. This was a plane equation
- **Simple explanation of projection transformation:** The plane equation $y = a+b_1x_1+b_2x_2$ was properly transformed into a straight line: $y = a+b_3x_3$, among them:

$$b_3^2 = b_1^2+b_2^2,\ b_3x_3 = b_1x_1+b_2x_2 \tag{1}$$

Minimum variance method to change point: It was supposed that: $X_1, X_2,...,X_N$ was independent for each other; t was time interval per unit. Steps for minimum variance method of change point search were:

- **Making I = 2,...,N, this sample was divided into two sections:** $X_1, X_2,...,X_{i-1}$ and $X_i, X_{i+1},...,X_N$. Then calculating the arithmetic mean value $\bar{X}_{i1}$, $\bar{X}_{i2}$ and the statistics of each section of samples:

$$S_i = \sum_{t=1}^{i-1}(x_t - \bar{X}_{i1})^2 + \sum_{t=i}^{N}(x_t - \bar{X}_{i2})^2 \tag{2}$$

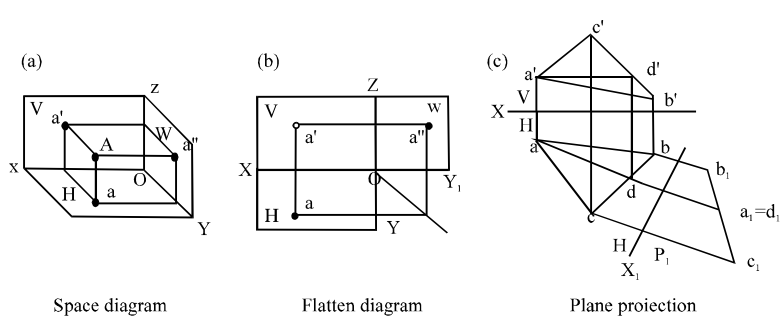

Fig. 1(a-c): (a)Point in three-projectional space, (b) Point flatten to the same projection plane V and (c) Plane flatten to the same projection plane V

- **Calculating statistics:**

$$\bar{X} = \sum_{t=1}^{N} x_t / N \text{ and } S = \sum_{t=1}^{N} (x_t - \bar{X})^2 \quad (3)$$

- **Calculating expected value:**

$$\begin{aligned} E(S - S_i) &= E(N^{-1}(i-1)(N-i+1)(\bar{X}_{i1} - \bar{X}_{i2})^2) \\ &= \sigma^2 + N^{-1}(i-1)(N-i+1)(E\bar{X}_{i1} - E\bar{X}_{i2})^2,\ i = 2,3,\ldots,N \end{aligned} \quad (4)$$

- **Calculating maximum value:**

$$E(S - S^*) = \max_{2 \le i \le N} E(S - S_i) \quad (5)$$

where, $S^* = \min(S_2,\ldots,S_N)$, the change point estimation value of $\hat{m}$ was the corresponding value i of S*

- **Taking α as significant level of inspection, calculating the value of C:** Follow could be obtained by Probability limit theorems:

$$\lim_{n\to\infty} P\left(\frac{S - S^*}{\sigma^2} < 2\ln\ln n + \ln\ln\ln N - \ln\pi + z\right) = \exp(-2e^{-z/2}) \quad (6)$$

If σ^2 was known, for the given $\alpha>0$, making $\exp(-2e^{-z/2}) = 1-\alpha$. This solution was:

$$C = \sigma^2 (2\ln\ln N + \ln\ln\ln N - \ln\pi - 2\ln(-0.5\ln(1-\alpha))) \quad (7)$$

If σ^2 was unknown in above equation, the following estimate was:

$$\hat{\sigma}^2 = S^*/(N - 2\ln\ln N - \ln\ln\ln N - 2.4) \quad (8)$$

- If $S-S^*>C$, H_0 was negative, namely, there was change point; otherwise H_0 was accepted

MODEL APPLICATIONS

Data source: Data came from an aviation turbojet engine. The experimental engine started to test for 200 h life span in July 2011 and the data were carried out during the 200 h life span test (there were an additional 40 h after 200 h, totally 240 h), each test 1 h as a stage. Change point model in this study was set up by parameters of electrostatic induction signal (E), lubricating oil consumption (C), lubricating oil pressure (P) from stage 76 to 127, as shown in Fig. 2 and 3.

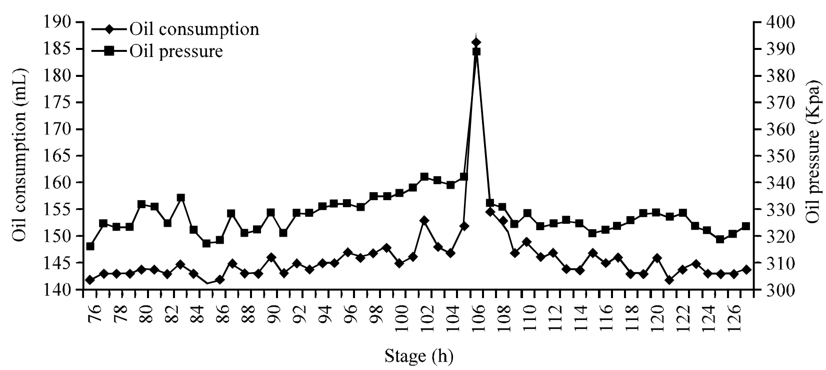

Fig. 2: Data of lubricating oil consumption (C) and lubricating oil pressure (P) from 76 to 127 stages

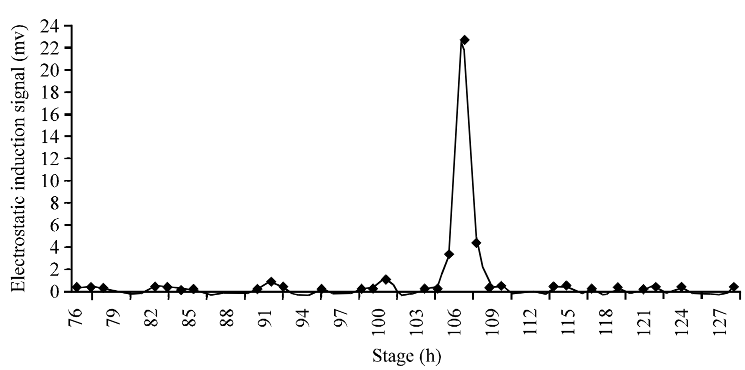

Fig. 3: Data of electrostatic induction signal (E) from 76 to 127 stages

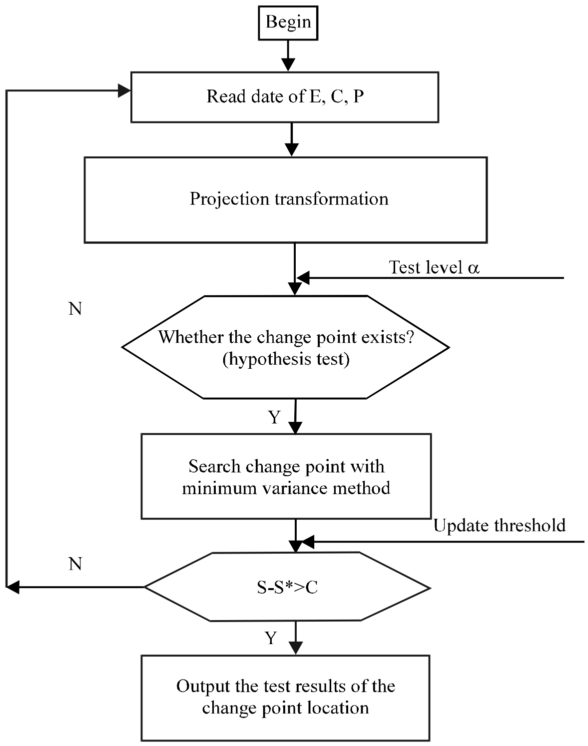

Fig. 4: Change-point searching process diagram

After projection transformation, new straight line was accumulated into: $E_i = a+bX_i+e_i$, $E_i = a+b_1C_i+b_2P_i$, $b^2 = b_1^2+b_2^2$, $bX_i = b_1C_i+b_2P_i$, (X_i, E_i). $i = 76,77,...,127$ were 52 times observations. When $i = 76,77,...,m-1$, (X_i,E_i) obeys linear regression model, that was $E_i = a_3+b_3X_i+e_i$ and then, when $i = m, m+1,...,127$, (X_i, E_i) obeys another linear regression $E_i = a_4+b_4X_i+e_i$. Here, e_i was random error of the model. If either of $a_3 \neq a_4$ or $b_3 \neq b_4$, the regression equation was changed at the point m and m was called the transition point.

Algorithm process: Change point with algorithm was shown in minimum variance method and the flow charts was followed as Fig. 4.

RESULTS AND DISCUSSION

Setting test level α was 0.05 in simulation, according to the algorithm and searching flow chart, the results showed S = 4612.587, S* = 3145.373, C = 1382.458, that was, S-S*>C, so there was a change point in source data. The statistical analysis by SPSS (Haijie and Er, 2008) had confirmed the algorithm results, discussions were given as followed:

Table 1: Model correlation description and residual series independence tests

Model	R	R^2	Adjusted R^2	Durbin-watson
1	0.742	0.551	0.549	2.003
2	0.731	0.534	0.531	1.946
3	0.589	0.347	0.341	1.769

Table 2: Explanation ability with significant level from independent variables to dependent variable

Model	F	Sig.
1	19.323	0.000
2	29.484	0.000
3	56.245	0.000

Table 3: Three types of values for predicted electrostatic induction signal (E) and its residuals statistics

Values	Minimum	Maximum	Mean
Predicted value	-0.53700	21.70480	1.2065
Residual	-5.47845	16.57378	0.0000
Std. predicted value	-0.95400	6.22200	0.0000
Std. residual	-1.84300	5.57600	0.0000

- As shown in Table 1, Model 1 indicated the regression model before change point occurred, the Adjusted R Square was 0.549
- Model 2 indicated the regression model after change point occurred with its Adjusted R Square 0.531
- Model 3 indicated the regression model of the whole data with Adjusted R Square 0.347 which was more smaller than model 1 and 2

This indicated the fitting degree of model 3 was unacceptable as well as change point existed in data structure.

Moreover, the Durbin-Watson values of the three models were 2.003, 1.946, 1.746, all of them were nearly 2 which made great sense for random error e_i.

As shown in Table 2, each model reached a significant level of 0.00 which indicated that the regression model was meaningful.

Furthermore, F value indicated the explanation ability from independent variables to dependent one and with the increase of F value, the explanation ability was much stronger. The F values of model 1 and 2 were 14985.456, 13247.391 while model 3 was 8018.586. Accordingly, the F values of model 1 and 2 were much larger than model 3 so that, explanation ability to the dependent variable from source variables was rather poor, namely, there were anomalous values in source data.

As shown in Table 3, the minimum and maximum of Predicted Value for electrostatic induction signal(E) from model 3 were -0.5370 and 21.7048 while its mean value was 1.2065. From this table, mean residual value was 0.000, Std. mean residual value was 0.000, these indicated that the residual distribution satisfied the zero mean assumption.

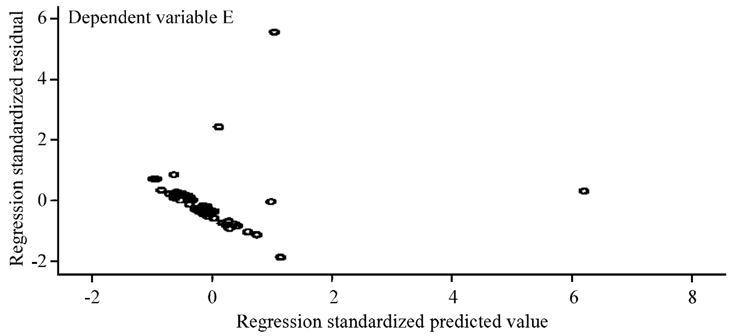

Fig. 5: Scattered plots of residual distribution

Finally, Table 3 showed Std. Residual value from model 3 was 5.576, out of normal range[-3,+3]. This verified there was change point in sample data. Figure 5 showed scattered plots of residual distribution.

CONCLUSION

With change point theory and actual test data of aero-engine, change point occurring time of oil consumption was found. Engine condition detection would be made a great development with less maintenance cost and more safety. Conclusions were given as below: Firstly, because of its higher accuracy and instantaneity, change point searching could effectively detect quantitative change occurring time of components before qualitative faults. Based on the above algorithm, whether the abnormity trend of engine working condition was occurred or not can be judged ahead, there must be early warning on condition-based maintenance. Secondly, it was difficult for binary regression model to make 3D scattered-points diagram and analyze space types intuitively, projection transformation could change binary regression model into one regression change-point model simply and effectively as well as reduce computation. Thirdly, there was lubricating oil leakage fault to the change point. When inspecting, it was found oil leaked at starting generator. After replacing the sealing ring and reinstalling starter generator, the 107th phase started for testing work. Obviously, OC decreased and the change point test results corresponded with the actual condition. Fourthly, electrostatic induction signal confirmed the corresponding fault. Although the electrostatic pulse signal appeared in 106th phase and other phases, but there were differences of pulse amplitude, times as well as emerging time. The pulse maximum amplitude of 106th stage was 22.7 mv and it demonstrated oil leakage fault. Fifthly, because it was difficult to eliminate the influence of fault cause (residual oil particles in gas path) in a short time, though oil consumption was decreased, there were also larger abnormal points in 107th. Sixthly, the statistical analysis by SPSS had confirmed the change point searching results. In the data of change point included, values of Adjusted R Square, Durbin-Watson, F distribution were smaller while Std. Residual value is bigger out of normal range[-3,+3]. It indicated there were anomalous values in source data. Lastly, from the views of engine faults detection technology, electrostatic induction technique was the development and supplement for vibration monitoring technology. Because of the complex engine structure, it was difficult to study its vibration characteristics by analytical method or experimental method, moreover, the vibration sensor signals often reflected in overall vibration and the abnormal vibration was also a macro reaction system, resulting in difficulties of fault location. Electrostatic monitoring technology was just the one that could monitor components or materials level. Early warning could be provided for initial fault state through monitoring gas path charge level changes in real-time. There must be a new theoretical method and technical means for real-time online monitoring and diagnosis of engine gas path components.

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