

2012 International Conference on Applied Physics and Industrial Engineering Aero-Engine Condition Monitoring Based on Support Vector Machine

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Abstract

The maintenance and management of civil aero-engine require advanced monitor approaches to estimate aero-engine performance and health in order to increase life of aero-engine and reduce maintenance costs. In this paper, we adopted support vector machine (SVM) regression approach to monitor an aero-engine health and condition by building monitoring models of main aero-engine performance parameters(EGT, N1, N2 and FF). The accuracy of nonlinear baseline models of performance parameters is tested and the maximum relative error does not exceed $\pm 0.3\%$, which meets the engineering requirements. The results show that SVM nonlinear regression is an effective method in aero-engine monitoring.

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Keywords: aero-engine condition monitoring, baseline model, SVM

1. Introduction

Because advanced aero-engine systems are becoming increasingly more complex, the reliable aero-engine condition monitoring (ECM) and fault identification schemes are demanded urgently [1][2]. ECM is the process of recognizing when a system has begun to operate outside its original design limits. Aero-engine health performance can be evaluated better by detecting abnormal behavior in engine related parameters and using prognostic approaches to predict its behavior in the upcoming flights. In fact, the monitoring of parameters can identify abnormality in time, which can effectively avoid fault occurring and reduce maintenance costs.

At present, the research methods for aero-engine condition monitoring are very little. In [3], multivariate linear regression method based on QAR (quick access recorder) data is applied in identification of the influence factors on aircraft fuel flow. The assessment of accuracy of verification shows that the established model has better verification effect and provides the reference for improving the control efficiency of fuel consumption and controlling the fuel cost. However, this model has some disadvantages in the application. On the one hand, relationship of aero-engine performance parameters and engine altitude (PALT) is nonlinear, which will affect accuracy of monitoring by using multivariate linear regression method. On the other hand, this model considers too many factors to ensure its stability. In [4], the neural networks are adopted to predict aero-engine performance parameters. They

have played an important role in resolving the failure problems of aero-engine. However, this neural networks method can be only applied to the specified aero-engine type.

In summary, it is often the case that those methods are unavailable or the current mathematical models do not accurately describe the complex system to monitor aero-engine condition. SVM indicates its superior ability in solving nonlinear regression problem and avoiding the problem of networks structure selection and local minimum. Therefore, in this paper we develop a data driven method which employs support vector machines nonlinear regression to build aero-engine monitoring model using a set of training data and testing data. The experimental results show that the approach can provide an effective monitoring in aero-engine performance and health.

2. Support Vector Machine Nonlinear Regression

Support vector machine based on structural risk minimization principle which is a new data mining technology, is first introduced by Vapnik in the late 1960s as a part of the development of statistical learning theory [5]. It is an effective method to deal with problems with limited samples and high dimension. After the rapid development in recent years, it has become one of the core algorithms in statistic learning. SVM shows a unique potential on the aspect of regression analysis.

In this section, we concisely review the fundamental of SVM. T is the training set,

$$T = \{(x_1, y_1), \dots, (x_l, y_l)\} \in (R^n \times Y)^l \quad (1)$$

where x_i is input vector, y_i is output vector, $i=1,2,\dots,n$. For nonlinear regression, SVM is to find a nonlinear mapping Φ . The Φ maps the input space to a high dimensional feature space. Then an optimal line regression function can be expressed as

$$f(x) = \omega \bullet \Phi(x) + b, \quad (2)$$

Therefore, given an input x , the corresponding output y can be obtained.

To calculate ω, b , the minimizing problem is given as follows.

$$\min_{\omega, b, \xi, \xi^*} \frac{1}{2} \|\omega\|^2 + C \sum_{i=1}^l (\xi_i + \xi_i^*) \quad s.t. \quad (3)$$

$$(\omega \bullet \Phi(x) + b) - y_i \leq \varepsilon + \xi_i, i = 1, 2, \dots, l,$$

$$y_i - (\omega \bullet \Phi(x) + b) \leq \varepsilon + \xi_i^*, i = 1, 2, \dots, l,$$

$$\xi_i \geq 0, \xi_i^* \geq 0, i = 1, 2, \dots, l,$$

where ξ, ξ^* are the usual slack variables, C is regularization constant, ε is insensitive coefficient.

The problem above can be transformed as the following dual optimization problem:

$$\min_{\alpha, \alpha^*} \frac{1}{2} \sum_{i,j=1}^l (\alpha_i^* - \alpha_j^*)(\alpha_i - \alpha_j) K(x_i, x_j) + \varepsilon \sum_{i=1}^l (\alpha_i^* + \alpha_i) - \sum_{i=1}^l y_i (\alpha_i^* - \alpha_i) \quad s.t. \quad (4)$$

$$\sum_i (\alpha_i - \alpha_i^*) = 0 \quad \text{where } \alpha_i, \alpha_i^* \text{ represent the Lagrange multipliers,}$$

$$0 \leq \alpha_i, \alpha_i^* \leq \frac{C}{l}, i = 1, 2, \dots, l,$$

$$K(x_i, x_j) = \Phi(x_i) \bullet \Phi(x_j) \quad (5)$$

is kernel function.

Thus, the nonlinear regression function can be shown as the formula (6).

$$f(x) = \sum_{i=1}^l (\alpha_i^* - \alpha_i) K(x_i, x_j) + b \quad (6)$$

3. Aero-Engine Condition Monitoring

3.1 The Principle Of Aero-Engine Condition Monitoring

Aero-engine condition is monitored through the aerodynamic thermal parameters. The aero-engine condition monitoring system uses steady state cruise in-flight taken by aircraft communications address and reporting system (ACARS). The data are corrected to sea level static condition, and compared with baseline of a particular aero-engine configuration. The difference between the in-flight data and the baseline is referred to as a “raw” delta. These deltas are plotted in the form of trends to identify possible aero-engine malfunctions, instrumentation and installation problems [6].

The baselines of aero-engine performance parameters are confidential, our aim of research is to find the baseline models to monitor civil aero-engine condition.

In most aero-engine maintenance and health assessment actions, the performance parameters are applied to monitor aero-engine condition, mainly include EGT, N1, N2, and FF. According to ECM and aero-engine mechanism, those parameter baseline values are determined by EPRI, PALT and TAT. Such that the EPRI, PALT and TAT values are adopted to predict the EGT, FF, N1 and N2 baseline values. The direct comparison of the data is visually poor for engineers to observe. In this paper, we adopt the method of relative error to estimate the goodness of fit. The relative error is calculated by the equation (7):

$$RERR = \frac{y_i - \bar{y}_i}{y_i}, \tag{7}$$

where y_i is original data and \bar{y}_i is the predict data of y_i by SVM.

The requirement on project monitoring is relative error less than $\pm 1\%$. Otherwise, alarming is given for maintainers to check whether the aero-engine is fault.

3.2 Parameters Correction

Aero-engine can be better monitored by related aero-engine performance parameters. Those parameters mainly include Exhaust Gas Temperature (EGT), Fan Speed (N1 and N2) and Fuel Flow (FF). Then we will use baseline approach based on data to established aero-engine condition monitoring model. The development trend of aero-engine performance parameters will be predicted in the upcoming flights.

The flight environment is varying widely in different flights. The aero-engine performance parameters values are also varying widely in different flight environment, which makes the different flights can not be compared directly. Therefore, according to ECM the aero-engine performance parameters values should be corrected to sea level static condition by the following equations.

$$EGT_cor = (EGT_obs + 273.15) / \theta T_2 \tag{8} \quad N_1_cor = N_1_obs / (\theta T_2)^{0.5} \tag{9}$$

$$N_2_cor = N_2_obs / (\theta T_2)^{0.5} \tag{10}$$

$$FF_cor = FF_obs / \delta (\theta T_2)^{0.5} \tag{11}$$

where

$$\theta T_2 = (TAT + 273.15) / 288.15 \tag{12}$$

$$\delta = P / P_0 \tag{13}$$

P is the 2th station atmospheric pressure of compressor (PAMB), and P_0 is the standard sea level atmospheric pressure, which equals to 101325pa.

$$EGT_base = EGT_cor - \Delta EGT \tag{14} \quad N_1_base = N_1_cor - \Delta N_1 \tag{15}$$

$$N_2_base = N_2_cor - \Delta N_2 \tag{16}$$

$$FF_base = FF_cor - \Delta FF \tag{17}$$

where $_base$ is parameter baseline value, $_cor$ is parameter corrected value, $_obs$ is parameter observed value.

4. The Monitoring Model Based On Svm

4.1 Data Description

In this paper, the aircraft communications address and reporting system (ACARS) data offered by an aircraft maintenance company in Beijing is used for this analysis. The ACARS data are taken by EHM and can be divided into three flight modes: Take off mode, Cruise mode and Landing mode. The ACARS data includes various aero-engine performance parameters that are recorded at different sampling intervals. The PW4077D aero-engine 110 flights data are analyzed. The 100 flights data in 2008 is used as training set and the 10 flights data in 2009 is used as testing set.

4.2 The Analysis Of Svm Regression Algorithm For Earo-Engine Performance Parameters

The particular steps of support vector regression algorithm are given as follows:

Step 1: To give the training set(1)

Input variable is the indictors of aero-engine performance parameters such as EPRI, PALT and TAT. The performance parameters EGT, N1, N2 and FF are output indictors.

Step 2: To select the appropriate kernel function.

There are three kinds of kernel functions at present: polynomial kernel function, radial basis kernel function, sigmoid kernel function. The radial basis kernel function

$$K(x_i, x_j) = \exp\left(\frac{-\|x - y\|^2}{2\sigma^2}\right) \quad (18)$$

is selected for this paper.

Step 3: To construct and solve the optimization problem (4).

The optimal solution

$$\bar{\alpha} = (\bar{\alpha}_1, \bar{\alpha}_1^*, \dots, \bar{\alpha}_l, \bar{\alpha}_l^*) \quad (19)$$

is obtained, $i=1,2,\dots,n$. If $\bar{\alpha}_i, \bar{\alpha}_i^*$ are all nonzero, (x_i, x_j) is called support vector. Otherwise, it is called nonsupport vector.

Step 4: To construct decision function.

Then, we need to construct decision function

$$f(x) = \sum_{i=1}^l (\bar{\alpha}_i^* - \bar{\alpha}_i) K(x_i, x_j) + \bar{b} \cdot \quad (20)$$

where \bar{b} can be calculated by selecting the $\bar{\alpha}_j$ or $\bar{\alpha}_k^*$ from the open interval $(0, \frac{C}{l})$.

If the $\bar{\alpha}_j$ is selected, then

$$\bar{b} = y_j - \sum_{i=1}^l (\bar{\alpha}_i^* - \bar{\alpha}_i) K(x_i, x_j) + \varepsilon \quad (21)$$

If the $\bar{\alpha}_k^*$ is selected, then

$$\bar{b} = y_k - \sum_{i=1}^l (\bar{\alpha}_i^* - \bar{\alpha}_i) K(x_i, x_j) - \varepsilon \quad (22)$$

Step 5: To check the accuracy of training.

In this paper, the accuracy of training is estimated by calculating mean squared error

$$MSE = \sqrt{\frac{1}{n} \sum_{k=1}^n (y_i - \bar{y}_i)^2} \quad (23)$$

where n is the capacity of sample data set, y_i is original data and \bar{y}_i is the predict data of y_i by SVM. Finally, the relative error between original data and predict data is applied to monitor the aero-engine performance and health.

5. Results

With Matlab software platform, we use SVM to predict the aero-engine performance parameters. According to the steps of the algorithm described above, the training data and testing data are fitted. In this paper, we take N1 and EGT as examples to analyze. The other parameters can be fitted in the same method.

The fitting plot of performance parameters N1 is shown in figure 1.

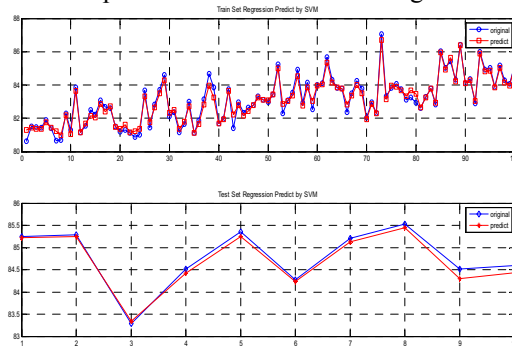


Fig.1 The fitting plot of performance parameters N1

$$MSE = 0.256733$$

The comparative table between original baseline value and predict baseline value is given.

TABLE I THE COMPARATIVE TABLE OF N1

No.	Original Values	Predict Values	Relative Error
1	85.2500	85.2200	0.000352
2	85.2800	85.2500	0.000352
3	83.2900	83.3400	-0.000600
4	84.5100	84.4200	0.001065
5	85.3500	85.2500	0.001172
6	84.2700	84.2300	0.000475
7	85.2000	85.1200	0.000939
8	85.5300	85.4500	0.000935
9	84.5100	84.3000	0.002485
10	84.6000	84.4300	0.002009

The fitting plot of performance parameters EGT is shown in figure 2.

$$MSE = 1.366778$$

The comparative table between original baseline value and predict baseline value of EGT is given.

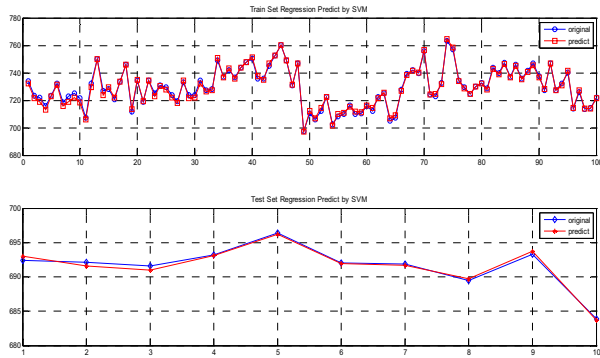


Fig.2 The fitting plot of performance parameters EGT

TABLE II THE COMPARATIVE TABLE OF EGT

No	Original Values	Predict Values	Relative Error
1	692.3700	693.0600	-0.001000
2	692.1200	691.6100	0.000737
3	691.5600	690.9800	0.000839
4	693.2100	693.1200	0.000130
5	696.3700	696.2600	0.000158
6	692.0800	691.9800	0.000144
7	691.9000	691.6700	0.000332
8	689.4700	689.7000	-0.000330
9	693.3200	693.7100	-0.000560
10	683.9000	683.6600	0.000351

In table III, the accuracy comparison of nonlinear regression model, neural networks and SVM methods is expressed.

TABLE III THE METHODS ACCURACY COMPARISON

Method	Average relative error
Multivariate line regression model	0.001353
neural networks	-0.081360
SVM nonlinear regression model	0.000918

It can be seen from table 3 that the average relative error of Multivariate nonlinear regression model and neural networks is larger than error of SVM. It exposes that SVM based on structural risk minimization principle is suited for monitoring.

The baselines of aero-engine performance parameters are found accurately based on SVM, the “raw” delta could be calculated, so that we monitor civil aero-engine condition without manufacturer’s monitoring system.

6. Conclusions

A data driven aero-engine condition monitoring technique based on support vector machines nonlinear regression is presented and applied to monitor and identify the common aero-engine system of PW4077D. The experimental examples show that the support vector machine nonlinear regression model is able to fit the performance parameters with a high degree of accuracy and can

effectively monitor aero-engine condition and health. The analysis result of aero-engine condition monitoring can provide a layout for trending of related flight parameters for upcoming flights and identify significant behavior disparities for the maintainer to evaluate and make future maintenance decisions, which assists to improve engine life and reduce down time. In the future, the improving of model accuracy is under investigation. In addition, we will investigate the development of support vector machine nonlinear regression approach in online monitoring.

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