Research Article

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Performance degradation detection method of aeroengine fuel metering device

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Abstract: In order to realize the safety status monitoring and health management of aeroengine fuel system, a performance degradation detection method of aeroengine fuel metering device was proposed. Aiming at the internal leakage, external leakage, static friction increase, dynamic friction increase, differential pressure controller degradation, and other common performance degradation modes of fuel metering devices, a residual life estimation method based on random forest support vector regression (RF-SVR) was proposed. The SVR model optimized by RF feature selection is used to estimate the remaining life of components. The simulation results show that the mean square error of remaining useful life (RUL) estimation is less than 1.8, the average percentage error is less than 3%, and it has high prediction accuracy. Therefore, the evaluation and verification of the internal leakage health indicators proposed in this article screen out the health indicators that are sensitive to changes in performance degradation parameters but insensitive to changes in environmental and structural parameters and provide decision-making reference for onsite maintenance of engine fuel metering devices.

Keywords: aeroengine, fuel metering device, health management

1 Introduction

Modern aeroengines require accurate control of fuel flow in order to give full play to the engine performance potential and ensure its safety. A fuel metering device is one of the key accessories of aeroengine as an actuator to realize accurate fuel supply for the engine [1]. In the civil aviation engine industry, it is very important to improve the availability of products. Figure 1 shows the oil supply device of the aviation engine fuel system. The human and material resources wasted by engine component failure and emergency maintenance caused by failure have brought serious economic losses to the operation of Airlines [2]. Especially when the passenger plane stops at an airport lacking maintenance equipment and personnel, the long delay of the flight and the cost of manpower and material resources scheduling will increase exponentially. Therefore, the research and development of civil turbofan engine Prognostics and health management system has become an important task for civil engine manufacturers [3].

As the core component of aeroengine control system, the performance of aeroengine fuel system directly affects the normal operation of the engine and even affects the safety and reliability of aircraft operation [4]. At the same time, modern aeroengines require accurate control of fuel flow to give full play to the performance potential of aeroengines. As the core component of the engine fuel system, the fuel metering device undertakes the important task of providing accurate metering fuel and servo fuel for the engine. The fuel metering device operates under the impact of high temperature and high-pressure fuel, with a poor working environment, prone to performance degradation and failure, resulting in flight mission delay, unnecessary economic losses, and even engine out of control during operation, endangering flight safety and causing casualties [5,6]. Therefore, the research on the health management of aeroengine fuel metering device is of great significance.

On this basis, based on the research on the health management of civil turbofan engine fuel systems, taking the fuel metering device as an example, this article carries out the research on health management technology from the aspects of performance degradation mode analysis, health index selection, performance degradation detection, residual life estimation, and so on. The performance degradation detection method based on Mahalanobis distance and the remaining service life estimation method based on
RF-SVR are proposed. The effectiveness of the method is verified by simulation based on the fuel system model of the engine. Considering the environmental uncertainty, this method puts forward a health index with high sensitivity to performance degradation. At the same time, the remaining service life of the metering device can be predicted based on the health index data, so as to realize the predictive maintenance of the fuel system, improve the safety of flight operation, and reduce the operation cost of civil aviation flights.

2 Literature review

China is vast, and the climate temperature difference between the north and the south and the four seasons changes greatly. The change in oil temperature will cause the change in fuel density, viscosity, flow coefficient, and mechanical coupling characteristics and then cause the change of component characteristics such as constant pressure differential valve and even metering flow in the metering device. There is little disclosure on the research on the health management technology of aero-engine fuel systems. Rudreshaiah et al. established the mathematical model of the engine fuel system and used the difference between the calculated value of the model and the feedback value of the sensor to compare the difference with the threshold to realize the fault diagnosis of various components of the fuel system. This method strongly depends on the system model, is limited by the accuracy of the model, and has poor robustness [7]. Hopkinson proposed to judge whether the metering device and its sensor have fault based on the fuel metering device model and locate the fault based on the engine inverse model, which realizes the isolation of fuel metering device fault and linear variable differential transformer (LVDT) sensor fault, but this method does not consider the impact of environmental uncertainty on the system. Depending on the fixed mathematical model of fuel metering devices, misdiagnosis and missed diagnosis easily occur [8]. Shao et al. proposed to design the fault residual generator of the main fuel metering device based on the Kalman filter and simulated and verified the actuator stuck, electrohydraulic servo valve stuck, and drift faults, which effectively reduced the fault false alarm rate and missing alarm rate, but this method is powerless for the diagnosis of wear, leakage, and other performance degradation of the metering device [9]. Kiran made detailed work on failure mode analysis and health index selection of main fuel pump, fuel metering device, and other components of civil turbofan engine fuel system, constructed fuel system agent model based on SVR Kriging method, and verified the health index system considering environmental and structural uncertainty [10]. Fernandez Garcia and coauthors analyzed the common failure modes of the components of the fuel metering device of the
civil turbofan engine, proposed the corresponding health indicators for the typical internal leakage performance degradation of the metering device, constructed the agent model based on the SVR Kriging method, and verified the proposed health indicators considering the environmental and structural uncertainty. The effectiveness of the health index is verified, but no reliable health index is proposed for the performance degradation mode of increasing static and dynamic friction of the metering device [11]. Dan et al. studied the characteristics of the metering device and the law affected by the fuel temperature to avoid abnormal engine fuel control or even failure of the metering device caused by too high or too low oil temperature [12]. Singh et al. believe that computer digital simulation technology has low cost and short cycle and has become a very important means in the process of design and development [13]. Keenan et al. provide a complete platform for system engineering design, which can establish the model of complex multidisciplinary systems on the same platform, and carry out simulation calculation and in-depth analysis on this basis [14]. Margalit et al. can use this software to build the simulation model of the whole fuel metering device, simulate the working process of the device under various typical working conditions, analyze the simulation results, and then provide the basis for the structure and parameter optimization of the device [15]. Hamedi et al. proposed that the engine fuel metering device test system designed and constructed based on the existing flight/propulsion integrated control simulation platform can simulate various typical working conditions such as speed change and various pressure changes during aeroengine operation and can measure and collect various test data [16].

3 Research methods

3.1 Analysis of performance decline mode

Fuel metering unit (FMU) is the core component of the aeroengine fuel system. It undertakes the important task of supplying fuel to engine combustion chamber and has a direct impact on the performance of aeroengine. Therefore, this article takes the fuel metering device as an example to carry out research on health management [17]. FMU is composed of an electrohydraulic servo valve, metering valve, and differential pressure control assembly. The differential pressure control assembly can ensure that the differential pressure before and after the oil outlet hole of the fuel metering valve remains unchanged so that the fuel flow at the outlet of the metering valve is only determined by the opening area of the metering valve, so as to realize the accurate control of fuel flow output. The FMU control structure is shown in Figure 2.

3.2 Selection of health indicators

FMU is an electrohydraulic actuator composed of an electrohydraulic servo valve, metering valve, and differential pressure control components. Generally, the flow gain curve of electrohydraulic servo valve can directly reflect the performance change of electrohydraulic actuator, but in the aviation engine fuel system, the electrohydraulic servo valve is not equipped with a flow sensor. It is impossible to directly monitor the performance change of an electrohydraulic actuator from a measurable signal [18]. To solve this problem, a performance monitoring method based on the current velocity curve is proposed in this article. In practical engineering, the following positive proportional relationship is observed between the actuating speed of the metering valve of the electrohydraulic actuator and the output flow of the electrohydraulic servo valve, as shown in formula (1):

\[ Q = VS, \]

where \( Q \) is the output flow of the electrohydraulic servo valve, \( V \) is the actuating speed of the metering valve, and \( S \) is the action area between servo oil and metering valve. Since the FMU is not equipped with a speed sensor,
the actuating speed of the metering valve can be obtained by differential operation of the displacement signal output by the LVDT sensor. Therefore, the flow change of the electrohydraulic servo valve can be indirectly reflected by monitoring its speed change, so as to reflect the performance change of the FMU. In order to obtain the operation data close to the real working condition, based on the AMESim matlab joint simulation method and considering the uncertainty of environmental parameters and model parameters, as shown in Table 1, Monte Carlo simulation is carried out to obtain the current velocity data, which is smoothed and piecewise linear fitted to obtain the current velocity gain curve.

### 3.3 Performance degradation detection method based on Mahalanobis distance

#### 3.3.1 Global exception parameter construction

In order to detect the performance degradation of fuel system components, it is necessary to construct the component global anomaly parameter ($G_Z$) according to the component health index. First, based on Monte Carlo simulation, the health index data of each component of the fuel system under health state are obtained, and its Gaussian distribution parameters are calculated, as shown in formula (2):

$$M(i) = [\mu_i^{\text{health}}, \sigma_i^{\text{health}}],$$

where $\mu_i^{\text{health}}$ is the mean value of the $i$th health index in the healthy state, and $\sigma_i^{\text{health}}$ is the standard deviation of the $i$th health index in the healthy state. After the measured health index value of the component is obtained, the corresponding abnormal parameters are calculated based on the following formula, as shown in formula (3):

$$Z_i = \frac{H_i - \mu_i^{\text{health}}}{\sigma_i^{\text{health}}},$$

where $H_i$ is the $i$th extracted health index value and $Z_i$ is the abnormal parameter value corresponding to the index. The abnormal parameter value is calculated corresponding to each health index to the abnormal parameter vector $Z$ corresponding to the component, as shown in formula (4):

$$Z = [Z_1, Z_2, Z_3, \ldots, Z_n].$$

By calculating the Mahalanobis distance between the abnormal parameter vector in the current state and the abnormal parameter vector sample set in the healthy state, the global abnormal parameter $G_Z$ is obtained.

#### 3.3.2 Selection of detection threshold

After obtaining the global abnormal parameters of the fuel system components, their values are compared with the threshold value $T$. When the global abnormal parameter value exceeds the limit, it is considered that the performance of the components has deteriorated. In this process, the selection of the threshold value is particularly important. It is usually calculated based on the following formula, as shown in formula (5):

$$T = u + A s,$$

where $u$ is the mean value of the global abnormal parameters of the components in the healthy state, $s$ is its standard deviation, and the size of the coefficient $A$ is determined in combination with the actual data and engineering needs.

### 3.4 FMU performance degradation detection

Due to space limitations, this study mainly considers two performance degradation modes of internal leakage and external leakage of the metering valve. The global abnormal parameter $G_Z$ of FMU is obtained based on the Monte Carlo simulation method. In the healthy state, the distribution of internal leakage and external leakage of the metering valve is analyzed according to its global abnormal parameter distribution. When $A$ takes different values, the performance of the missing alarm rate and false alarm rate of the performance degradation detection algorithm is shown in Table 2. In order to maximize the performance of the detection algorithm, the detection threshold coefficient of FMU is taken as 3.

### Table 1: Model uncertainty parameters

| Parameter                  | Uncertainty distribution ($\mu$, $\sigma$) |
|----------------------------|------------------------------------------|
| Fuel temperature/°C        | (40, 15)                                 |
| Equivalent mass/kg         | (1.15, 0.06)                             |
| Natural frequency of servo valve/Hz | (30, 0.5)               |
| Metering valve diameter/mm | (35, 0.5)                                |
| Friction factor/(n/(M/s))  | (100, 1.5)                               |
| A     | Internal leakage | Leakage | A     | Internal leakage | Leakage |
|-------|------------------|---------|-------|------------------|---------|
|       | False alarm rate (%) | Missing alarm rate (%) |       | False alarm rate (%) | Missing alarm rate (%) |
| 0     | 42.14            | 0.07    | 0     | 41.88            | 0.03    |
| 1     | 14.42            | 0.06    | 1     | 14.15            | 0.02    |
| 2     | 3.17             | 0.10    | 2     | 3.23             | 0.11    |
| 3     | 1.05             | 0.24    | 3     | 0.86             | 0.10    |
| 4     | 0.12             | 7.68    | 4     | 0.10             | 7.24    |
| 5     | 0.03             | 34.66   | 5     | 0.03             | 50.04   |

### 3.5 Estimation of remaining service life

#### 3.5.1 Random forest (RF)

RF is a pattern recognition algorithm based on the classification tree proposed by Breiman. It improves the prediction accuracy of the model by summarizing a large number of classification trees. RF model is essentially a classifier composed of a large number of decision trees, which are mutually independent and identically distributed random vectors. Finally, all decision tree results vote to obtain the output results of RF [19, 20]. The specific implementation process of RF is as follows:

1. Based on the boost resampling method, the RF extracts 63.2% of the samples from the original training sample set each time to generate a sub-sample set, and each sub-sample set corresponds to a classification tree. The remaining unselected samples are out-of-bag data (OOB). OOB error data are used to evaluate the classification accuracy of the classifier.

2. Based on a single sub-sample set, a single classification tree is generated. At each node of the tree, \( m (m < M) \) eigenvectors are randomly selected from the \( M \) eigenvectors of the sample, usually \( m = \text{int}(\sqrt{M}) \), that is, \( m \) takes the downward integer of \( \sqrt{M} \). And make each classification tree grow fully without pruning until each tree can accurately classify the training set or classification attributes are exhausted.

3. In the test stage, the RF model summarizes the classification results of each classification tree based on the voting principle.

#### 3.5.2 Support vector regression (SVR)

SVR is a generalization of support vector machine in regression [21, 22]. SVR maps the feature vector of the original sample set from low-dimensional space to high-dimensional space and performs regression analysis on the sample set based on high-dimensional space. The regression function is shown in formula (6):

\[
f(x) = w\varphi(x) + b,
\]

where \( w \) is the weight vector, \( \varphi \) is the mapping implicit function, \( x \) is the eigenvector in the original space, and \( b \) is the offset. In order to solve \( w \) and \( b \), the minimization function is established, as shown in formula (7):

\[
\min \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}|f(x_i) - y_i|,
\]

where \( C \) is the penalty coefficient, \( N \) is the number of training samples, \( x_i \) is the eigenvector of the ith training sample, \( f(x_i) \) is the predicted value of the ith training sample, and \( y_i \) is the real value of the ith training sample.

### 4 Result analysis

#### 4.1 Simulation of performance degradation law

FMU is essentially a hydraulic actuator, and its performance degradation law is assumed as a function related to actuation distance and flight time during simulation verification, as shown in formula (8):

\[
D = \left( k_0(0) + k_F \cdot \sum \Delta a \right) \times 100%,
\]

where \( D \) is the performance degradation percentage of FMU, \( \sum \Delta a \) is the historical actuation distance of the metering valve, \( k_F \) is the constant coefficient, \( k_0(0) \) is its initial default value (not 0), and \( F \) is the flight time. The performance degradation curve obtained by simulation is shown in Figure 3.

#### 4.1.1 Remaining useful life (RUL) estimation simulation verification

Taking the two performance degradation modes of internal leakage and external leakage of FMU as examples, this
The article takes the abnormal parameter vector in the two cases as the training set to train the RF model and establish the classifier. Monte Carlo sampling is carried out based on the fuel system model to obtain the health data of the fuel metering device in the random health state, test the performance of the classifier as a test data set, and evaluate it based on the sensitivity and specificity of its main performance indicators [23]. Eight health index parameters are selected for FMU. Here, the RF feature selection algorithm is used to reduce the dimension of FMU health index, eliminate redundant features, and obtain the importance scores of each health index under the two performance degradation modes of internal leakage and external leakage, as shown in Figures 4 and 5.

According to the importance score, select \( Y_1, Y_2, x_{V0} \) as the training sample set to train the internal leakage SVR model, and select \( S_1, S_2, x_{V0} \) as the training sample set to train the external leakage SVR model [24]. The penalty parameter \( C \) and kernel function parameter \( g \) of the SVR model are obtained by small-scale traversal optimization. Based on the performance degradation law in this article, the component health data corresponding to flight time are generated, and its remaining service life is predicted based on the SVR model [25].

According to the analysis of Figures 6 and 7, the estimated mean square error of the RF-SVR regression model is less than 1.8, and the average absolute
percentage error is less than 3%. This method can accurately estimate the performance degradation and remaining service life of fuel metering devices according to the health data and give early warning when the remaining life is less than 30% of the whole life cycle and about 400H. This method can accurately estimate the performance degradation and remaining service life of fuel metering devices according to the health data, give early warning when the remaining life is less than 30% of the whole life cycle and about 400H, and prompt the engine maintenance personnel to repair it.

5 Conclusion

Through simulation and test, this article studies the performance degradation detection of aeroengine fuel metering device, analyzes the influence of fuel temperature on metering characteristics, and obtains the following conclusions: the regression features of SVR model are selected based on RF, the redundant features are eliminated, and the estimation accuracy of SVR model is improved. It is verified based on the simulation data of the mechanical and hydraulic model of the fuel system. The mean square error of RUL estimation is less than 1.8, and the average percentage error is less than 3%. It has high prediction accuracy and has important reference significance for the predictive maintenance of the fuel system.

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