Aero-engine Health Monitoring Method Based on E-Bayes and DNN Fusion Decision

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Abstract. As a complex system, aero-engine running condition affects flight safety, so aero-engine health monitoring is necessary. We proposed an aero-engine health monitoring method based on E-Bayes method and deep neural network (DNN). Firstly, based on the fleet operation records, E-Bayes was used to calculate the reliability of aero-engine operation. Secondly, we constructed the DNN network base on the parameters collected by sensors and reliability parameter, fused the DNN results under different parameters according to the characteristics of different health condition of the aero-engine, and finally the fusion decision model based on the E-Bayes method and DNN was realized. We trained and verified the network with 9616 aero-engine running data samples contaminated by noise. The average accuracy was 96.15\%, which shows that this method has good robustness.

Introduction

Health monitoring means the identification and characterization of operation condition and performance level, which can be used as the basis for operation and maintenance plan. As a typical complex system, aero-engine install a large number of sensors, which can collect parameters real time during the operation process, and provide conditions for aero-engine health monitoring. A good health monitoring system can reduce flight risk and predict the development of performance degradation and potential failure.

In the field of health monitoring, some research work has been carried out. HAN \cite{b1} used e-Bayes method to calculate the reliability of rocket engine. Bocchetti \cite{b2} established a competitive failure reliability analysis model for marine diesel cylinder liners. Bedford \cite{b3} analyzed the characteristics of various competitive failure reliability assessment models from a statistical point of view. Lehmann \cite{b4} used performance degradation monitoring and fault data, adopted degradation threshold shock (DTS) model to establish the relationship between sudden failure and performance degradation and environmental impact factors. LI \cite{b5} studied the reliability analysis and evaluation methods of polymorphic systems and multiple failure modes. Bagdonavičius \cite{b6} studied the nonparametric estimation method of competitive failure model by using the semi update process of linear performance degradation model. Chemweno \cite{b7} combined with the prior function proposed by the experts and the observation evidence based on the empirical data, derived the posterior distribution function of the risk measurement related to the equipment failure. Berge\textsuperscript{1} \cite{b8} gave a
method of coalbed methane joint data mining based on state detection data and historical maintenance management data.

Health Monitoring Evaluation Framework

Reliability Analysis Method of Aero-engine

In the process of aero-engine operation, with the accumulation of flight cycles, the health degradation of aero-engine usually conformed to a certain rule which can be characterized by operating state detection parameters, such as thrust, fuel flow, EGT, high-pressure rotor speed, low-pressure rotor speed, etc., Those parameters constitute the air path monitoring system, oil path monitoring system, vibration monitoring system, etc. In addition, the number of flight hours and flight cycles before the performance degradation of the same engine in the same fleet are generally similar, which approximately obeys normal distribution. It is possible to provide statistical reference of the health monitoring and performance reliability based on the operation records. This reference can used to enhance the performance of running state parameter monitoring, reduce the risk caused by sensor failure, noise pollution and other special circumstances.

Health Monitoring Level Evaluation Method for Aero-engine

E-Bayes models is based on Bayes models, constructs an E-Bayes prior distribution to obtain the posterior distribution, which has a good performance of no-failure data. Compared with the single hidden layer neural network, deep neural network (DNN) increases the number of hidden layers and nodes, improves the complexity of the model. It has a better effect on feature extraction of complex data. With the degradation of aero-engine performance, the changing rate of performance monitoring parameters is also change, so the features extract effect of learning rate-changed neural network is better than learning rate-fixed neural network. Based on those theories, we proposed a method of aero-engine health monitoring evaluation based on E-Bayes models and deep neural network fusion decision:

1) In the view of the operation and operation records of the same type of aero-engine with similar service environment in the fleet, Statistics the number of flight cycles before health degradation overrun of the same engine in the fleet to build E-Bayes models. Then calculate the unreliability of aero-engine operation under different flight cycles.

2) Build the dataset that based on the original parameters sample set collected by sensors during the operation of aero-engine and the unreliability calculated by E-Bayes method, which represent the health degradation rule from installing to performance degradation overrun. This process can be divided into three operation periods on the basis of expert information: reliable life period(RLP), accelerated degradation period(ADP) and near overrun period(NOP). Choose the appropriate number of hidden layers and nodes, establish the deep neural network,

3) Use the sections of original sample segmentation to train neural network. Then, use the rest of the samples to verify the accuracy of the network performance. Use different network learning rate setting retrain network to fix different health period better, realize the fusion decision of aero-engine health monitoring.
**Evaluation Method of aero-engine Health Monitoring**

The health monitoring assessment method in this paper include the condition monitoring assessment model based on deep neural network, the reliability assessment model based on E-Bayes method, and the DNN model enhanced by E-Bayes method

**Assessment Model Based on Deep Neural Network**

The DNN we built has 5 layers, contains an input layer, 3 hidden layers and an output layer. The structure of this network is depicted in Figure 1.

\[ h_i = (h_1, h_2, h_3, \ldots) = \begin{cases} f(w_i x + b_i) & i = 1 \\ f(w_i h_{i-1} + b_i) & i = 2, 3 \end{cases} \]

\[ y = (y_1, y_2, y_3, \ldots) = s(w_3 h_3 + b_3) \]

We used Softmax function as the activation function of the output layer, so the outputs from the deep neural network is:

\[ loss = -\sum(x \ln y) \]

Back propagation is used to adjust the network. Learning rate is set to $\theta$. On each iteration, weight vector and bias units are updated:

\[
\begin{aligned}
    w_i &= w_i + \Delta w_i = w_i - \theta \frac{\partial loss}{\partial w_i} \\
    b_i &= b_i + \Delta b_i = b_i - \theta \frac{\partial loss}{\partial b_i}
\end{aligned}
\]
Repeat this iteration until the network shows good convergence effect, so we can get the trained deep neural network.

**Assessment Model Based on E-Bayes Method**

For products obey Weibull distribution, reliability distribution function is:

\[ R(t) = \exp\left(-\left(\frac{t}{\eta}\right)^m\right) \]  \hspace{1cm} (5)

Where \( m > 0 \) and \( \eta > 0 \) are shape parameter and scale parameter.

To fix failure probability \( p(t) = P(T > t) \), we need to determine prior distribution of \( p(t) \). We consider that the prior distribution of \( p(t) \) obeys Beta distribution function with two parameters, and its probability density function is:

\[ f(p \mid \alpha, \beta) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} p^{\alpha-1}(1-p)^{\beta-1} = B(\alpha, \beta) \]  \hspace{1cm} (6)

where \( B(\alpha, \beta) \) is:

\[ B(\alpha, \beta) = \int_0^1 t^{\alpha-1}(1-t)^{\beta-1} dt \]  \hspace{1cm} (7)

On the basis of health monitoring and maintenance records of those aero-engines, it is considered that \( \alpha = 1, \beta \sim U[1, c] \). Probability density function of \( p(t) \) is:

\[ f(p \mid b) = \beta(1-p)^{\beta-1} \]  \hspace{1cm} (8)

In reference [1], the definition of E-Bayes estimation of is given. Before degradation overrun, the number of aero-engines, which flight cycle number is more than \( t_i(t_1 < t_2 < \cdots < t_k) \), is denoted as \( s_i \), so E-Bayes estimation of \( p(t_i) \) is:

\[ \hat{p}(t_i) = \frac{\ln\left(\frac{s_i + c + 1}{s_i + 2}\right)}{c-1} \]  \hspace{1cm} (9)

To optimize the estimate results, we set a weight parameter:

\[
\omega = \begin{cases} 
t_i n_i / \sum_{i=1}^{k} t_i n_i & i < k \\ 
\frac{s_i - s_{i+1}}{s_i} & i = k 
\end{cases}
\]

(10)

The E-Bayes estimation of reliability \( \hat{R}(t) \) and unreliability \( \hat{F}(t) \) is:

\[ \hat{R}(t) = \exp\left(-\left(\frac{t}{\hat{\eta}}\right)^{\hat{m}}\right) \]  \hspace{1cm} (11)

\[ \hat{F}(t) = 1 - \exp\left(-\left(\frac{t}{\hat{\eta}}\right)^{\hat{m}}\right) \]  \hspace{1cm} (12)

Where \( \hat{m} \) and \( \hat{\eta} \) are estimate parameters of Weibull distribution, and can be denoted:
\[
\begin{align*}
A &= \sum_{i=1}^{k} \omega_i \ln \left[ \ln \left( \frac{1}{1 - \tilde{p}_i} \right) \right] \\
B &= \sum_{i=1}^{k} \omega_i \left\{ \ln \left[ \ln \left( \frac{1}{1 - \tilde{p}_i} \right) \right] \right\}^2 \\
C &= \sum_{i=1}^{k} \omega_i \ln(t_i) \\
D &= \sum_{i=1}^{k} \omega_i \ln(t_i) \ln \left[ \ln \left( \frac{1}{1 - \tilde{p}_i} \right) \right]
\end{align*}
\]

\[\hat{\eta} = \exp \left( \frac{BC - AD}{B - A^2} \right)\]
\[\hat{m} = \left( \frac{D - AC}{B - A^2} \right)^{-1}\] 

(13)

**Experimental Results**

We used 9616 monitoring samples collected from 50 aero-engines of a certain type during installing and degradation overrun, including the number of flight cycles and 21 kinds of sensor acquisition parameters contaminated with sensor noise. Base on the expert information, three health level classifications are labeled according to the degree of health monitoring.

| Engine | t | Sensor1 | Sensor2 | … | Sensor21 | Label |
|--------|---|---------|---------|---|----------|-------|
| 1      | 1 | 449.44  | 555.32  | … | 8.8071   | RLP   |
| 1      | 2 | 445     | 549.9   | … | 6.2665   | RLP   |
| …      |   |         |         |   |          |       |
| 1      | 149| 445     | 550.49  |   | 6.2285   | NOP   |
| 2      | 1 | 518.67  | 642.04  | … | 23.2326  | RLP   |

**Reliability Estimation Base on E-Bayes Method**

The number of flight cycles is counted as samples, and the distribution of it before the health degradation overrun is obtained:

| t   | 140 | 150 | 160 | 170 | 180 | 190 | 200 | 210 | 220 | 230 | 240 | 250 | 260 | 270 | 280 | 290 |
|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| s   | 50  | 49  | 43  | 40  | 35  | 32  | 24  | 15  | 12  | 9   | 7   | 5   | 5   | 3   | 2   | 1   |

On the basis of expert information and maintenance record, we set \( c \) to 4, then applied E-Bayes model to calculate the failure probability \( \hat{p}(t) \) and the unreliability \( \hat{F}(t) \). The results are as follows:

| Sample | Sensor | Sensor | … | Sensor | \( \hat{F}(t) \) | Label |
|--------|--------|--------|---|--------|-----------------|-------|
| s      | 1      | 2      | … | 21     | 6.2593          | 0.97% | NOP |
Health Level Classification Based on DNN Enhanced by E-Bayes Method

Add $\hat{F}(t)$ into data, then selected 20% samples as test samples randomly, and the rest as training samples.

We used 21 kinds of sensor acquisition parameters, unreliability $\hat{F}(t)$ and health level classifications labels from training samples as the input of deep neural network. After adjusting and optimizing, the learning rate is set to 0.02 and the initial learning weights diameter is set to 0.01, and trained the initial weights of hidden layer and output layer. Then used BP method to fine tune and optimize the network continuously. Repeat this iteration, after 350 iterations, we obtained the trained deep neural network.

In order to evaluate the quality of the network, 1924 testing samples without labels were input into the deep neural network, classifying the health levels to verify the classification results.

Table 4. Classification results.

| Samples | Sensor1 | ... | $\hat{F}(t)$ | Label | Scored probabilities for “NOP” | Scored probabilities for “ADP” | Scored probabilities for “RLP” | Classifying label |
|---------|---------|-----|--------------|-------|-------------------------------|-------------------------------|-------------------|------------------|
| 7       | 445.00  | ... | 0.16%        | RLP   | 0.000649                      | 0.071488                      | 0.927862          | RLP              |
| 58      | 489.05  | ... | 12.68%       | NOP   | 0.979676                      | 0.020072                      | 0.000251          | NOP              |
| ...     |         |     |              |       |                               |                               |                   |                  |

The results show that, based on the samples contaminated with sensor noise, the average accuracy of the deep neural network is 94.80%. Classification error mainly occurs at the edge of two adjacent health level, and as the health degradation continues to develop and leave the edge between health levels, the probability of classification error will be reduced. It can be considered that the deep neural network shows a good result in aero-engine operation state analysis.

We compared this network with DNN without enhanced by E-Bayes method. Keeping the hidden layer structure and optimal learning rate of the original network unchanged, we used the same training samples without unreliability $\hat{F}(t)$ to retrain the network, used BP method to adjust, and obtained the new trained deep neural. Then use the same test samples unreliability $\hat{F}(t)$ to evaluate the new network quality. The result shows that, compared with the DNN without enhanced by E-Bayes method, the average classification accuracy based on the noisy samples is increased 1.12%, and the recognitions efficiency of samples in the accelerated degradation period greatly increased 6.6%. Especially, the classification probability of the new network for each health level is closer to 0 or 1, means the classification fuzziness of the network decreases and the credibility of the classification results increases. The distribution of classification probability of each health level from each network is shown in the Figure below.
Table 5. Average accuracy compared.

|                | Enhanced DNN | Non-enhanced DNN | Difference |
|----------------|--------------|------------------|------------|
| Average accuracy | 94.80%       | 93.68%           | 1.12%      |

Network Enhance by Learning Rate Changing

Reset learning rate to 0.1, retain the deep neural network and assess it accuracy. The results show that in a high learning rate setting, the classification accuracy for samples in “NOP” and “RLP” is increased, and the classification accuracy for samples in “ADP” decrease meanwhile. The average accuracy decreased to 94.04%.

Figure 3. Distribution matrix of classification results.
To get better estimation results of whole 3 periods in aero-engine operation, the final classification result is:

\[
\text{Classification result} = \max[\text{"RLP"}_{0.1}, \text{"ADP"}_{0.02}, \text{"NOP"}_{0.1}]
\]  

(14)

Where "\(X\)_i" means the scored probabilities for “\(X\)” in the learning rate set to \(i\). The average accuracy we get from the fusion decision of deep neural network finally is 96.15%.

**Conclusion**

A deep neural network enhanced by E-Bayes method has been studied. Combined with the estimation of the unreliability based on the operation records obtained by E-Bayes model and different estimation results under different learning rate, this model can estimate health level of aero-engine operation, and realized E-Bayes integrated with DNN fusion decision.

The results show that this method improves the accuracy and credibility of the evaluation based on samples contaminated with sensor noise, which shows good robustness. The effectiveness and feasibility of this method were proved by an example, which is helpful to reduce the risk of aero-engine operation and improve the efficiency of condition-based maintenance.

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