Aeroengine Performance Degradation Evaluation Method Based on Hierarchical Bayes Integrated with DNN Fusion Decision

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Abstract. According to the performance degradation law of aeroengine in operation, we proposed a method of aeroengine performance degradation evaluation based on the fusion decision of Hierarchical Bayes method (HB) and deep neural network (DNN). Hierarchical Bayes method was used to build the aeroengine reliability model. Then Based on the aeroengine operation monitoring parameters and reliability model, we used deep learning method to extract the performance degradation law and to evaluate aeroengine performance level, realized the fusion decision of engine performance degradation assessment. 9467 monitoring samples, contaminated with sensor noise, collected from 50 aeroengines was used to evaluate the quality of the network, and the average accuracy is 92.01%. The results showed that this method showed good robustness and reduced the risk of the evaluation results error caused by noise.

Keywords. Aeroengine, Performance degradation, Fusion decision, Deep learning, Hierarchical bayes method.

1. Introduction
As the core of aircraft, aeroengine's operation performance will directly affect flight safety and operation efficiency of aircraft and airlines. Aeroengine is a typical complex system, the relationship between the performance degradation law of aeroengine and its state detection parameters is complex, and it is difficult to monitor hidden failures and potential failure trends. The traditional aeroengine performance monitoring methods mostly used a key single parameter, such as Exhaust Gas Temperature (EGT) to evaluate the performance degradation. It is easy to be interfered by noise or individual abnormal parameter, so sometimes it can’t reflect the real running state of aeroengine.

In the field of operational state assessment, some research work has been carried out. Han [1] used e-Bayes method to calculate the reliability of rocket engine. Vlokp [2] used proportional intensity model (PIM) to predict the residual life of the equipment. Wang [3] built a general residual life prediction model by using nonlinear, non-white noise filtering method. Gebracel [4] used Bayes update method, real-time state monitoring information and component life distribution function to predict the residual life under exponential performance degradation. Baruah [5] used hidden Markov model (HMM) to evaluate the system state and calculate the residual life base on monitoring signals. Li [6] used the combination regression method and the health monitoring information between the two overhauls, combined with the linear regression and the quadratic regression to predict the residual life of the engine. Gebracel [7] used dynamic wavelet neural networks (DWNN) to predict residual life.
2. Performance Degradation Evaluation Framework

2.1. Reliability Analysis Method of Aeroengine
In the process of aeroengine operation, with the accumulation of flight cycles, the performance degradation of aeroengine 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 constituted 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 were generally similar, which approximately obeys normal distribution. So it is possible to provide statistical reference of the performance degradation degree 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.

2.2. Performance Level Evaluation Method for Aeroengine
Hierarchical Bayes models is based on Bayes models, constructs a multi-layer 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, so it has a better effect on feature extraction of complex data. Based on those theories, we proposed a method of aeroengine performance degradation evaluation based on Hierarchical Bayes models and deep neural network fusion decision:

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

2) Build the dataset that based on the original parameters sample set collected by sensors during the operation of aeroengine and the unreliability calculated by Hierarchical Bayes method, which represent the performance 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). Establish the deep neural network, choose the appropriate number of hidden layers and nodes, 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, realize the fusion decision of aeroengine performance degradation.

3. Evaluation Method of Aeroengine Performance Degradation
The performance degradation assessment method in this paper include the condition monitoring assessment model based on deep neural network, the reliability assessment model based on Hierarchical Bayes method, and the DNN model enhanced by Hierarchical Bayes method.

3.1. Assessment Model Based on Deep Neural Network
The DNN we built have 5 layers, contains an input layer, 3 hidden layers and an output layer. The structure of this network is depicted in figure 1.
This network is a fully-connected neural network, and each hidden layer have the formula:

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

$h_i$ is the $i$-th hidden layer; $w_i$ and $b_i$ are the weight vector and the bias units for the $i$-th layer; $x$ is the inputs; $f(\cdot)$ is the activation function.

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

$$y = (y_1, y_2, y_3, ...) = s(w_3 h_3 + b_3) \quad (2)$$

We used cross entropy as the loss function, it can be expressed as:

$$loss = - \sum(x \ln y) \quad (3)$$

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

$$\begin{cases} w_i = w_i + \Delta w_i = w_i - \theta \frac{\partial loss}{\partial w_i} \\ b_i = b_i + \Delta b_i = b_i - \theta \frac{\partial loss}{\partial b_i} \end{cases} \quad (4)$$

Repeat this iteration until the network shows good convergence effect, so we can get the trained deep neural network.

**Figure 1.** The structure of DNN.
3.2. Assessment Model Based on Hierarchical Bayes Method

For products obey Weibull distribution, reliability distribution function is:

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

(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:

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

(6)

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

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

(7)

On the basis of performance degradation and maintenance records of those aeroengines, it is considered that \( \alpha = 1, \beta \sim U[1, c] \). So probability density function of \( p(t) \) is:

\[ f(p \mid c) = \int_1^c f(p \mid \beta) f(\beta) \, d\beta = \int_1^c B(1-p)^{\beta-1} \, d\beta \]  

(8)

Before degradation overrun, the number of aeroengines, which flight cycle number is more than \( t_i (t_1 < t_2 < \cdots < t_k) \), is denoted as \( s_i \), so the likelihood function of failure probability \( p(t_i) \) is:

\[ L \left( 0 \mid p_i \right) = (1-p_i)^{s_i} \]  

(9)

where 0 means there is no failure before degradation overrun.

According to Bayes’ theorem, the posterior density function of failure probability \( p(t_i) \) is:

\[ f \left( p_i \mid s \right) = \int_0^1 f(p_i \mid c) \mu(0 \mid p_i) \frac{f(p_i \mid c) \mu(0 \mid p_i)}{\int_0^1 f(p_i \mid c) \mu(0 \mid p_i) \, dp_i} \]  

(10)

So the Hierarchical Bayes estimation of \( p(t_i) \) is:

\[ \hat{p}(t_i) = \int_0^1 p_i f \left( p_i \mid c \right) \, dp = \frac{(s_i+1) \ln \left( \frac{s_i+c+1}{s_i+c} \right) - s_i \ln \left( \frac{s_i+c+1}{s_i+c+2} \right) \ln \left( \frac{s_i+c+2}{s_i+c+1} \right)} {c-1 \ln \left( \frac{s_i+c+2}{s_i+c+1} \right)} \]  

(11)

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

\[ \omega_i = t_i n_i / \sum_{i=1}^{k} t_i n_i \]

\[ n_i = \begin{cases} s_i & \text{if } 1 < i < k \\ s_i - s_{i+1} & \text{if } i = k \end{cases} \]  

(12)

So the Hierarchical Bayes estimation of reliability \( \hat{R}(t) \) and unreliability \( \hat{F}(t) \) is:

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

(13)

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

(14)

where \( \hat{m} \) and \( \hat{\eta} \) are estimate parameters of Weibull distribution, and can be denoted:
\[
A = \sum_{i=1}^{k} \omega_i \ln \left[ \ln \left( \frac{1}{1 - \hat{p}_i} \right) \right] \\
B = \sum_{i=1}^{k} \omega_i \left[ \ln \left( \frac{1}{1 - \hat{p}_i} \right) \right]^2 \\
C = \sum_{i=1}^{k} \omega_i \ln(t_i) \\
D = \sum_{i=1}^{k} \omega_i \ln(t_i) \ln \left( \frac{1}{1 - \hat{p}_i} \right) \\
\hat{\eta} = \exp \left( \frac{BC - AD}{B - A^2} \right) \\
\hat{m} = \left( \frac{D - AC}{B - A^2} \right)^{-1}
\]

(15)

4. Experimental Results
We used 9467 monitoring samples collected from 50 aeroengines 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. Based on the expert information, three performance level classifications are labeled according to the degree of performance degradation. Please see the table 1.

| 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   |
| …      |    |         |         |    |          |       |

| 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       |
| …      |    |         |         |    |          |       |

4.1. Reliability Estimation Based on Hierarchical Bayes Method
The number of flight cycles is counted as samples, and the distribution of it before the performance degradation overrun is obtained, as table 2:

| t  | 140 | 150 | 160 | 170 | 180 | 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 Hierarchical Bayes model to calculate the failure probability \( \hat{p}(t) \) and the unreliability \( \hat{F}(t) \). The results are as follows table 3:

| Samples | Sensor1 | Sensor2 | …  | Sensor21 | \( \hat{F}(t) \) | Label |
|---------|---------|---------|----|----------|-----------------|-------|
| 1       | 445.55  | 549.88  | …  | 6.2593   | 0.97%           | NOP   |
| 2       | 449.44  | 556.36  | …  | 8.7953   | 1.00%           | NOP   |
| …      |         |         |    |          |                 |       |

4.2. Performance Level Classification Based on DNN Enhanced by Hierarchical Bayes Method
Add \( \hat{F}(t) \) into data, then select 20% samples as test samples randomly, and the rest as training samples.

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We used 21 kinds of sensor acquisition parameters, unreliability $\hat{F}(t)$ and performance 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 0.05, 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. Please see the table 4.

In order to evaluate the quality of the network, 1893 testing samples without labels were input into the deep neural network, classifying the performance levels to verify the classification results.

### Table 4. Classification results.

| Samples | Sensor1 | ... | $\hat{F}(t)$ | Label | Scored probabilities for “ADP” | Scored probabilities for “ADP” | Scored probabilities for “RLP” | Classifying label |
|---------|---------|-----|-------------|-------|-------------------------------|-------------------------------|------------------|------------------|
| 31      | 518.67  | ... | 0.56%       | RLP   | 0.00005                       | 0.035581                     | 0.964414         | RLP              |
| 24      | 462.54  | ... | 2.99%       | NOP   | 0.99891                       | 0.00108                      | 0.00010          | NOP              |
| ...     |         |     |             |       |                               |                               |                  |                  |

The results show that, based on the samples contaminated with sensor noise, the average accuracy of the deep neural network is 92.01%. Classification error mainly occurs at the edge of two adjacent performance level, and as the performance degradation continues to develop and leave the edge between performance levels, the probability of classification error will be reduced, so it can be considered that the deep neural network shows a good result in aeroengine operation state analysis, as table 5.

We compared this network with DNN without enhanced by Hierarchical 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 used the same test samples unreliability $\hat{F}(t)$ to evaluate the new network quality. The result show that, compared with the DNN without enhanced by Hierarchical Bayes method, the average classification accuracy base on the noisy samples is increased 1.62%, and the recognition efficiency of samples in the accelerated degradation period greatly increased 11.10%. Especially, the classification probability of the new network for each performance 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 performance level from each network is shown in the figure 2 below.

### Table 5. Average accuracy compared.

| Enhanced DNN | Non-enhanced DNN | Difference |
|--------------|------------------|------------|
| Average accuracy | 92.01% | 90.39% | 1.62% |
5. Conclusion
A deep neural network enhanced by Hierarchical Bayes method has been studied. Combined with the estimation of the unreliability based on the operation records obtained by Hierarchical Bayes model, this model can estimate performance level of aeroengine operation, and realized DNN-HB 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 aeroengine operation and improve the efficiency of condition-based maintenance.

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