Comprehensive assessment of gas turbine health condition based on combination weighting of subjective and objective

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ABSTRACT
The multi-parameter comprehensive evaluation method of gas turbine can accurately grasp the state of engine health. Eight evaluation indicators were chosen from the condition of engine gas path degradation, the combustion system and the whole machine vibration. Aimed at the uncertainty of data information, the objective attribute weights were gotten based on the method of the combination of fuzzy clustering and information entropy by calculating the mutual information. In view of the equilibrium of data, another objective weights were gotten using the entropy weight method. Then the linear weighted sum method of the two was used to get the final objective weights of indicators. Subjective weights were obtained by analytic hierarchy process. Integrating the subjective and objective weights, multiplication combination method was used to determine the final weights. The multi-attribute comprehensive evaluation of gas turbine health status was carried out combined with a 2,000 hours test. Results show that the method can integrate the advantages of objective and subjective weighting methods, evaluation results are in line with the practical experience, which means it is a feasible way to the gas turbine condition assessment and maintenance decision.

INTRODUCTION
Safe, reliable, and economical gas turbine operation is of great concern to the user and manager. Increasing attention is being paid to relative status monitoring and condition-based maintenance. In the same operation condition, the change trend of engine performance parameters can objectively reflect performance deterioration. Therefore, evaluating the state according to monitoring information can predict the rate of performance deterioration and provide a scientific basis for maintenance decisions. According to the state monitoring information, the performance of a gas turbine can be determined objectively and accurately, which is the fundamental guarantee of high safety and reliability.

Gas turbine performance evaluation indicators include exhaust gas temperature, thermocouple dispersion, vibration value and so on. People are used to relying on a single parameter to evaluate an engine’s performance. This is simple, and it provides some basis for gas-turbine maintenance decisions. But as performance parameters often have complex interrelationships, only monitoring one index cannot fully reflect the performance of a gas turbine, and it can lead to the wrong decision. A multi-parameter comprehensive evaluation method is an effective solution to this problem.

There are two kinds of approach to determine the weight coefficient of a multi-parameter comprehensive assessment: subjective and objective [1]. The subjective approach is based on expert prior information on the weight of each attribute to make evaluations and comparisons. Common approaches of this type include the analytic hierarchy process (AHP) and Delphi method [2]. Although this method is quite explicable, there is an obvious subjective randomness. The objective approach determines the weight coefficient from objective information reflected in attribute indices. Examples include the common mean square error method, the maximum deviation method, and the entropy method [3-4]. This kind of method strengthens objectivity when determining the weight, but sometimes the results contradict practical experience, and they may not provide a reasonable explanation.

Fuzzy mathematics has been proved to be an effective method to solve uncertain decision-making problems [4]. And many scholars have applied fuzzy logic to gas turbine fault diagnosis [7-8]. The advantage of fuzzy mathematics in dealing with uncertain knowledge is that there is no loss of effective information. But it cannot determine the importance of various factors, and it needs a priori information to judge the relative weight. In information theory, the mutual information derived from entropy need not provide prior information and can determine the importance of various factors. Combining these two characteristics, Huang [9] proposed a multi-factor weight-allocation method based on objective information on entropy. Using this method, Zhang [10] calculated the comprehensive weights to analyze the performance of civil aviation engines.

In this paper, on the basis of above study, gas turbine health assessment indicators will be chosen from the condition of engine gas path degradation, the combustion system and the whole machine vibration, and the comprehensive assessment method of gas turbine health status integrating the advantages of subjective and objective weighting will be proposed. Aimed at the uncertainty and equilibrium of data, two objective attribute weights will be gotten based on the method of the combination of fuzzy clustering and information entropy and the entropy weight method. The final objective weights of indicators will be obtained by the linear weighted method of the two. Subjective weights will be obtained by analytic hierarchy process (AHP). Multiplication combination method integrating the subjective and objective weights will be used to determine the final weights. The evaluation of gas turbine health status will be carried out combined with an example.
CHOICE OF GAS TURBINE HEALTH STATUS

EVALUATION INDICATORS

Gas turbine health status evaluation index selection should satisfy the principle of the comprehensive, independence, comparability and operability, etc. For this reason, this paper chooses evaluation index from the aspects of gas path degradation condition, the combustion system state and the whole machine vibration state. Take a certain type of marine three-shaft gas turbine as an example. The schematic diagram is shown in figure 1. In figure 1 and paper below, LC, HC, B, HT, LT, PT respectively represent low pressure compressor, high pressure compressor, combustion chamber, high pressure turbine, low pressure turbine and power turbine. Each subscript number of letters in this paper represent corresponding section noted in figure 1.

Gas Path Degradation Condition Indicators of Whole Engine

The engine gas path degradation state assessment indexes can be made of heat loss index [11-12], power deficit index [11], exhaust gas temperature margin, thermal efficiency ratio [13].

The heat loss index $I_{hl}$ is defined as the ratio of the $T_6$ rise with respect to the design point:

$$I_{hl} = \frac{(T_6 - T_{6, exp})}{T_{6,d}}$$

where $T_6$ is measured value of low pressure turbine outlet temperature, $T_{6, exp}$ is expectancy obtained by the health gas turbine model in the same environment parameters and control conditions, and $T_{6,d}$ is design point temperature of rated condition.

The power deficit index $I_{pd}$ is defined as the ratio of the power deficiency to the design point power [11]:

$$I_{pd} = \frac{(N_{e, exp} - N_e)}{N_{e,d}}$$

where $N_e$ is the actual output power, $N_{e, exp}$ is the theoretical output power obtained by measured value $T_6$, $N_{e,d}$ is the designed point power of rated condition.

The thermal efficiency ratio $R_{lt}$ is defined [13] as

$$R_{lt} = \frac{\eta_l}{\eta_m},$$

where $\eta_l$ is thermal efficiency obtained by measured values, $\eta_m$ is the thermal efficiency predicted by the model at the same running conditions.

The exhaust gas temperature margin $M_{opt}$ of gas generator is defined as

$$M_{opt} = T_{6, obs} - T_0/\theta^*$$

where $T_{6, obs}$ is the threshold of $T_6$, $\theta^* = T_0/288.15$, $T_0$ is ambient temperature, and $\theta^*$ is an experiential index to eliminate the influence of environment temperature described in [14].

Gas Path Degradation Condition Indicators of Components

Gas path degradation condition of components can be characterized by degradation factors (defined as translation of characteristic curves caused by degradation) [15], such as low pressure compressor flow degradation factor $\delta\theta G_{pc}$, high pressure compressor flow degradation factor $\delta\theta G_{hp}$, high pressure turbine efficiency degradation factor $\delta\eta_{HP}$, low pressure turbine efficiency degradation factor $\delta\eta_{LP}$, and so on. The degradation factors can be solved by the method of linear or nonlinear Kalman filter.

Combustion System Status Indicators

There are 16 thermocouples temperature sensors along the circumference between the low-pressure turbine and power turbine in this type engine. The 1 # thermocouple temperature dispersion $S_1$ is defined as the difference between the highest and the lowest thermocouple temperature reading; the 2 # dispersion $S_2$ is defined as the difference between the highest with the second lowest reading; and the 3 # dispersion $S_3$ is defined as the difference between highest and the third lowest reading. To eliminate the influence of environment temperature, corrected dispersion is defined as

$$S = S_i/\theta^*$$

where $\theta = T_0/288.15$, $\theta^*$ is the same as Eq.(4). Thermocouple temperature dispersions reflect comprehensively the condition of the combustion chamber, fuel supply system and high temperature gas path.

Vibration State Indicators

The vibration acceleration sensors are set at the case of LC and HC and PT parts of the gas turbine. The vibration severity $V_i$ is defined as the root mean square value of LC vibration velocity effective value $V_{lc}$, HC vibration velocity effective value $V_{hc}$ and power turbine vibration velocity effective value $V_{pt}$, i.e.,

$$V_i = \sqrt{\sum V_{lc}^2 + V_{hc}^2 + V_{pt}^2}/3$$

Select the vibration intensity to characterize the gas turbine vibration condition.

WEIGHT ASSIGNMENT METHOD

Objective Weight Assignment Method Based on Information Entropy and Fuzzy Clustering

In this method, objective weights for each indicator are assigned combined with fuzzy clustering analysis and relative importance in the principle of rough set theory. Let’s clear a few concepts first.

(1) Information entropy. In the probabilistic approximation space $(U, X, P)$, $X = \{X_1, X_2, \ldots, X_n\}$ is a classification exported from the domain of discourse (i.e., the equivalence relation), and $P(X_i)$ is the probability in approximate space (that is the ratio of the cardinalities between each equivalent classification set and the domain). Then the uncertainty of the system can be represented by the information entropy, i.e.,

$$H(X) = - \sum_{i=1}^{n} P(X_i) \log_2 P(X_i)$$

(2) Conditional entropy. If $Y = \{Y_1, Y_2, \ldots, Y_k\}$ is another classification exported from the domain of discourse, the uncertainty of $X$ when $Y$ is obtained is the conditional entropy,
where \( p(X|Y) = \frac{|X \cap Y|}{|Y|} \), and \(|*|\) denotes the number of elements in the set \(*\), \(i = 1, 2, \ldots, m, j = 1, 2, \ldots, n\).

(3) Mutual information. The mutual information between \( X \) and \( Y \) is defined as
\[
I(X;Y) = H(X) - H(X|Y) = H(Y) - H(Y|X).
\]
It denotes the information of \( X \) obtained when \( Y \) is observed.

The method of multi-attribute weight distribution based on information entropy and fuzzy clustering is as follows:

1. Determine the decision matrix. Identify samples and factor indicators that must be addressed. Let \( X = \{X_1, X_2, \ldots, X_n\} \) be a set of \( n \) samples to be processed, and represent each sample by \( m \) indicators \( X_j = \{x_{ij}, x_{i2}, \ldots, x_{im}\} \). Then the samples required to be clustered can be represented by the decision matrix \( \{x_{ij}\}_{mxn} \).

2. Data normalization processing. The indices of a decision matrix usually relate to efficiency or cost type. The dimensions of indicators may differ, and indicators often vary in magnitude. To avoid the phenomenon that large numbers cover small numbers, the data must first be mapped into a certain range before clustering, which is called normalization processing. The normalized processing method is as follow [16]: for the cost type indicators (the smaller the better),
\[
r_{ij} = \frac{x_{ij} - \bar{x}_{ij}}{z_{ij} - z_{ij}} + 1 - \alpha,
\]
for the efficiency type indicators (the bigger the better),
\[
r_{ij} = \frac{x_{ij} - \bar{x}_{ij}}{z_{ij} - z_{ij}} + 1 - \alpha,
\]
where \( z_{ij} = \max_{1\leq m\leq m}(x_{ij}) \) and \( z_{ij} = \min_{1\leq m\leq m}(x_{ij}) \). To avoid an element taking a value of zero after normalization, an equilibrium factor \( \alpha \) in the range \([0,1]\) is introduced, and is set to 0.9 in this paper.

After normalization, the decision matrix becomes a fuzzy matrix,
\[
R = \{r_{ij}\}_{mxn}.
\]

3. Construct fuzzy similarity matrix. Using the maximum minimum method, the fuzzy matrix \( R \) is turned into the fuzzy similarity matrix \( S \):
\[
s_{ij} = \frac{\sum_{k=1}^{p} (r_{ik} \land r_{kj})}{\sum_{k=1}^{p} (r_{ik} \lor r_{kj})}.
\]

4. Construct fuzzy equivalent matrix. The transitive closure \( t(S) \) of fuzzy similarity matrix \( S \) is solved by the equivalent closure method [17], whose result is the fuzzy equivalent matrix \( E \).

5. Classification. The fuzzy equivalent matrix is truncated by the appropriate threshold \( \lambda_1 \), and the cut set matrix is obtained. The equivalent classifications can be obtained from the cut set matrix [17], and these are labeled as \( C_{\lambda_1} (k = 1, 2, \ldots, p) \). It does not take into account that the total is one class and each element is one class.

After one factor is deleted from all the indicators, repeat steps (3)-(5). The equivalent classifications corresponding to each threshold \( \lambda_2 \) are labeled as \( D_{\lambda_2} (k = 1, 2, \ldots, p) \).

6. Search for mutual information. Determine the mutual information at each threshold after removing the various factors.

When the classification is changed from the set \( C \) to the set \( D \) as a certain factor is removed, the influence on the positive domain of the object classification \( U \) in class \( C \) can be represented by the mutual information at each threshold, i.e.,
\[
I_{\lambda_1}(C;D) = H(C) - H(C|D).
\]

Eq.(12) expresses information on set \( C \) when set \( D \) is observed. The smaller \( I_{\lambda_1}(C;D) \) is, the more important the removed factor is. From the meaning of mutual information, after deleting one factor, if you can get more information from the initial classification, then the removed attribute contains less information for classification. Conversely, if you get less information from the initial classification, the information contained in the deleted attribute is greater. Therefore, the amount of mutual information obtained from the initial classification after deleting a factor is inversely proportional to the amount of information contained in the deleted factor. So, the reciprocal of mutual information can be used to indicate the relative amount of information contained in the deleted factor.

(7) Solve index information. The weighted reciprocal of mutual information at a different threshold is used to represent the index information contained in the deleted factor, i.e.,
\[
M_i = \sum_{k=1}^{p} \frac{1}{I_{\lambda_1}(C;D)}.
\]

(8) Distribute index weights. The index information is normalized to obtain the weight of each index, i.e.,
\[
w_{\text{IEFC}} = M_i/\sum_{i=1}^{n} M_i.
\]

**Objective Weight Assignment Based on Entropy Weight Method**

The greater an indicator fluctuation is, the greater the amount of information the indicator provides for comprehensive evaluation. Entropy weight method (EW) is based on each index fluctuation degree, using the relative strength entropy of the index value to calculate the weight of each index. The meaning of the relative strength entropy is as follows: take the proportion of the \( j \)th indicator of the sample \( X_j \) as the probability in information entropy formula, i.e.,
\[
p_j = r_j/\sum_{j=1}^{m} r_j.
\]
If the \( j \)th index values of the samples are the same, i.e., \( r_1 = r_2 = \cdots = r_m, p_j = 1/m \), it means the data are the most equalizing, and this index provides the least amount of information. So its weight is the least. The relative strength entropy of \( j \)th index is defined as
\[
e_j = \sum_{j=1}^{n} p_j \ln p_j = -\frac{1}{\ln m} \sum_{j=1}^{n} p_j \ln p_j.
\]
As \( \lim_{x \to 0} x \ln x = 0 \), \( p_j \ln p_j \) is set 0 when \( p_j = 0 \). The most value of \( e_j \) is 1. \( 1 - e_j \) denotes the numerical difference of \( j \)th indicator. The bigger the numerical difference is, the bigger the weight is. The method process is as follows:

1. Normalize the data of decision matrix, and get fuzzy decision matrix \( R = \{r_{ij}\}_{mxn} \).

2. Calculate the proportion of the \( j \)th indicator of samples, i.e.,
\[
p_j = r_j/\sum_{j=1}^{m} r_j.
\]

3. Calculate the relative strength entropy \( e_j \) of \( j \)th index.
Determine Ultimate Objective Weights by Weighted Sum Method

We get two kinds of objective weights from the uncertainty and the equilibrium of data above. As the two have the compensatory, we could obtain comprehensive objective weights by weighted sum method, i.e.,

$$w_{jOb} = \beta w_{jIEFC} + (1-\beta)w_{jH},$$

where $\beta \in [0,1]$ , and $j=1,2,\cdots,n$. We set $\beta = 0.5$ in this paper.

Determine Final Weights by Multiplication Combination Method

Objective weighting method does not consider the importance of the index itself, and the evaluation results are lack of convincing, while subjective weighting method (take AHP as an example) is difficult to avoid the influence of subjective randomness on the evaluation results. To make up for the defect of the two methods, we can combine the two kinds of weights. There are addition and multiplication in the combination weighting methods. Addition combination applies only on the occasions that there is linear compensability between indexes, while multiplication combination applies also when there is no compensability between indexes. So the multiplication combination method is adopted, i.e.,

$$w_j = \frac{w_{jOb} w_{jAHP}}{\sum_{j=1}^{n} w_{jOb} w_{jAHP}},$$

where $w_{jOb}$ is objective weight, and $w_{jAHP}$ is subjective weight obtained by AHP. Limited by space, the process of AHP is not expounded in this paper.

The fuzzy decision matrix $R$ multiplied by the index weight vector, the utility value of each sample can be obtained, i.e.,

$$Y = R \times W,$$

where $W = \{w_j\}$ , and $j=1,2,\cdots,n$.

**INSTANCE ANALYSIS**

A reliability test for the three-shaft marine gas turbine was carried out over 2,000 hours, during which three off-line cleanings were conducted. There are 16 thermocouples along the circumference between the low-pressure turbine and power turbine, so as to monitor the combustion chamber flame indirectly. Monitoring parameters include ambient temperature, atmospheric pressure, $p_1$, $p_2$, $p_3$, $T_1$, $T_2$, low pressure shaft speed, high pressure shaft speed, power turbine speed, pressure $\frac{\bar{N}}{e}$ and fuel flow rate, etc. Using gas turbine health state model [12] and test data, we get the indicators of the thermocouple dispersions $S_{1C}$, $S_{2C}$, $S_{3C}$, the vibration intensity $V_s$, heat loss index $I_{Hl}$, power deficit index $I_{pd}$, exhaust temperature margin of gas generator $M_{egt}$, thermal efficiency ratio $R_{th}$, low pressure compressor flow degradation factor $\delta G_{pC}$, high pressure compressor flow degradation factor $\delta G_{HC}$, high pressure turbine efficiency degradation factor $\delta \eta_{HT}$ and low pressure turbine efficiency degradation factor $\delta \eta_{LT}$ at rated working conditions, as shown in figures 2-5.
Fig. 4 Variation trend of overall engine performance degradation indexes

- (a) Flow capacity degradation factors of low pressure compressor
- (b) Flow capacity degradation factors of high pressure compressor
- (c) Exhaust gas temperature margin
- (d) Thermal efficiency ratio

The mean indicators data of the rated working conditions during the eight periods in the experiment are selected. Time periods are shown in Table 1.

<table>
<thead>
<tr>
<th>NO.</th>
<th>Periods (h)</th>
<th>remarks</th>
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<tbody>
<tr>
<td>I</td>
<td>0-25</td>
<td>initial run</td>
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<tr>
<td>II</td>
<td>576-595</td>
<td>before 1st cleaning</td>
</tr>
<tr>
<td>III</td>
<td>625-650</td>
<td>after 1st cleaning</td>
</tr>
<tr>
<td>IV</td>
<td>960-986</td>
<td>before 2nd cleaning</td>
</tr>
<tr>
<td>V</td>
<td>995-1,002</td>
<td>after 2nd cleaning</td>
</tr>
<tr>
<td>VI</td>
<td>1,268-1,275</td>
<td>before 3rd cleaning</td>
</tr>
<tr>
<td>VII</td>
<td>1,348-1,355</td>
<td>after 3rd cleaning</td>
</tr>
<tr>
<td>VIII</td>
<td>1,993-2,000</td>
<td>ending</td>
</tr>
</tbody>
</table>

Table 1: Time periods

The decision matrix is

\[
\begin{bmatrix}
71.5 & 54.4 & 36.2 & 5.84 & 0.06 & 0.04 & 136 & 0.97 & 0.009 & 0.010 & 0.005 & 0.010 \\
88.4 & 46.2 & 39.9 & 5.49 & 0.08 & 0.05 & 101 & 0.96 & 0.019 & 0.016 & 0.004 & 0.130 \\
95.7 & 55.7 & 53.1 & 7.34 & 0.04 & 0.02 & 127 & 0.98 & 0.016 & 0.012 & 0.021 & 0.114 \\
50.3 & 44.7 & 32.6 & 6.87 & 0.06 & 0.04 & 110 & 0.97 & 0.045 & 0.053 & 0.013 & 0.125 \\
64.9 & 64.4 & 53.3 & 6.48 & 0.05 & 0.05 & 120 & 0.96 & 0.016 & 0.026 & 0.011 & 0.105 \\
76.8 & 50.4 & 46.4 & 5.90 & 0.08 & 0.06 & 102 & 0.96 & 0.049 & 0.040 & 0.010 & 0.094 \\
47.8 & 38.7 & 35.6 & 4.18 & 0.06 & 0.03 & 120 & 0.98 & 0.037 & 0.031 & 0.017 & 0.109 \\
45.8 & 42.5 & 40.3 & 3.91 & 0.06 & 0.04 & 102 & 0.97 & 0.054 & 0.048 & 0.053 & 0.140
\end{bmatrix}
\]

The front six columns are cost type indicators, and the back six columns are efficiency type indicators, so they are normalized according to Eq.(9) and (10) separately, and the fuzzy decision matrix is
The initial information entropy of the system $H(C)$ is 0.8113 when $\lambda = 0.56_1$, according to Eq.(6). The conditional entropy $H(C | D_1)$ is 0 according to Eq.(7) when the parameter $S_{ic}$ is deleted at the same threshold. The mutual information at the same threshold is $I_{s_{ic}}(C, D_1) = 0.8113$, according to Eq.(12). Similarly, $I_{s_{ic}}(C, D_5) = 1.2988$, $I_{s_{ic}}(C, D_1) = 1.9056$, $I_{s_{ic}}(C, D_5) = 2.4056$, $I_{s_{ic}}(C, D_1) = 2.75$. The information for index 1 (i.e., $S_{ic}$) from Eq.(13) is $M_1 = 1.9802$.

Repeating the process above, we get $M_2 = 1.9802$, $M_3 = 2.4748$, $M_4 = 1.9802$, $M_5 = 1.9802$, $M_6 = 1.9802$, $M_7 = 1.9802$, $M_8 = 1.9802$, $M_9 = 1.9802$, $M_{10} = 1.9802$, $M_{11} = 1.9802$ and $M_{12} = 2.0873$. The weight distribution of each index is gotten by Eq.(14).

Objective weights obtained by the method of information entropy and fuzzy clustering (IEFC), objective weights by entropy weight method (EW), ultimate objective weights by weighted sum method (Ob), subjective weights by AHP and the final weights by multiplication combination method (Com) are all shown in Table 2. The utility values and sorts of engine health conditions during 8 periods obtained the single and comprehensive assessment methods are shown in table 3 (A represents utility value, B represents sort). The final utility values of the comprehensive evaluation based on multiplication combination method are $y_{s_{ic}} = (0.82, 0.28, 0.71, 0.40, 0.53, 0.21, 0.61, 0.34)$.

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<th>Table 2: Weight distribution</th>
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<tr>
<td>$S_{ic}$</td>
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<table>
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<th>Table 3: Utility values and sorts of engine health conditions during 8 periods</th>
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<td>$A$</td>
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From table 2, the weight of exhaust temperature margin of gas generator is bigger based on multiplication combination method. Considering the thermocouple dispersions, the vibration intensity, heat loss index, power deficit index, exhaust temperature margin of gas generator and thermal efficiency ratio, the comprehensive states sort, from superior to inferior, is: $y_1 > y_2 > y_3 > y_4 > y_5 > y_6 > y_7 > y_8$, and only considering exhaust temperature margin, the sort is...
$y_1 > y_2 > y_3 > y_4 > y_5 > y_6 > y_7 > y_8$. So, the two are not consistent. In general, the state of the gas turbine after a single cleaning is better than that before cleaning, and the state after three cleaning is better than that before cleaning as a whole. According to multiple indexes, the state at the beginning of the test is the best, and the state before the third cleaning (i.e. period VI) is the worst. Compared with period VI, although the indexes such as power deficit index $I_{\Delta e}$, exhaust temperature margin of gas generator $M_{\text{ope}}$, thermal efficiency ratio $R_{\text{e}}$, low pressure compressor flow degradation factor $\delta \tilde{\alpha}_{\text{c}}$, high pressure compressor flow degradation factor $\delta \tilde{\beta}_{\text{c}}$, high pressure turbine efficiency degradation factor $\delta \tilde{\eta}_{\text{t}}$, and low pressure turbine efficiency degradation factor $\delta \tilde{\eta}_{\text{lt}}$, are worse at the end of the test (i.e. period VII), corrected thermocouple dispersions $S_{1 e}$ and $S_{2 e}$ and vibration intensity index $\gamma$ are better at the end of the test, so the comprehensive evaluation of period VII is better than period VI.

CONCLUSION

This paper studies the comprehensive evaluation method of gas turbine state based on the combination of subjective and objective weights. Evaluation indicators of thermocouple dispersions, vibration intensity, heat loss index, power deficit index, exhaust temperature margin of gas generator, thermal efficiency ratio, compressor flow degradation factors and turbine efficiency degradation factors are chosen from the gas path degradation condition of whole engine and components and the whole machine vibration state. These indicators describe different aspects to grasp the state of engine health, certainly not always correlated with each other. Aimed at the uncertainty of data information, the objective attribute weights are obtained based on the method of the combination of fuzzy clustering and information entropy by calculating the mutual information. In view of the equilibrium of data, another objective weights are gotten using the entropy weight method. Then the linear weighted sum method of the two is used to get the final objective weights. Subjective weights are obtained by AHP method. Integrating the subjective and objective weights, multiplication combination method is used to determine the final weights. The multi-attribute comprehensive evaluation of gas turbine health status is carried out combined with a 2,000 hours test. Results show that the method can integrate the advantages of objective and subjective weighting methods, and evaluation results are in line with the practical experience, which means it is a feasible way to the gas turbine multi-index state-assessment and maintenance decision when the weight information is unknown.

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