Proceedings of the 41st Chinese Control Conference
July 25-27, 2022, Hefei, China

Equipment Health Assessment Based on AHP-CRITIC Dynamic Weight

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Abstract: Prognostics Health and Management (PHM) has become a hot research problem with the improvement of different equipment. Besides, it is significant to assess the health status of equipment in PHM because an accurate health assessment can guide maintenance plans for engineers. To accurately reflect equipment health status by an index, an assessment method based on AHP-CRITIC dynamic weight is proposed in this paper. Analytic Hierarchy Process (AHP) is a subjective method used to evaluate the importance of different indicators. The criteria importance through inter-criteria correlation (CRITIC) method is used to calculate the contrast intensity of the same indicator and the conflict between indicators and obtain the objective weights. A set of more scientific weights is gained by combining the weights obtained from AHP and CRITIC, respectively. Moreover, to reflect each indicator's real impact on overall health status, a dynamic weight adjustment mechanism is used. The case study of suction nozzles of a specific type of chip mounter shows that this method can reflect the health status accurately.

Key Words: Equipment health status assessment, Analytic Hierarchy Process, Criteria importance through inter-criteria correlation, Dynamic weight

1 Introduction

The health status of equipment, which originates from the medical field, reflects the ability of equipment to maintain a certain level of reliability and maintainability [1]. An accurate health status assessment is beneficial for predicting the degradation of equipment. Furthermore, degradation prediction is a vital part of prognostics and health management (PHM), which aims to provide an integrated framework for degradation prediction and maintenance policies to mechanical and electrical equipment [2].

In general, there are two different ways to describe the health status of equipment, one is to divide it into several health levels, and the other is to describe it with a numerical value. Since the latter approach avoids the problem of subjective classification and inaccuracy resulting from the former, using a numerical value to assess health status is preferred in current researches. A variety of health assessment approaches have been proposed in these years, which can be divided roughly into four categories. The first one is data fusion-based approaches, integrating various monitoring data to determine equipment health level [3–6]. The second one is fuzzy theory-based approaches [7, 8], due to the fuzziness of the health status. The third one is machine learning (ML)-based approaches, many ML techniques have been utilized to evaluate the health status of equipment, such as support vector data description (SVDD) [9], support vector machines (SVM) [10] and deep learning [11], etc. The fourth one is hybrid approaches [1, 12], which integrate the merits of different methods and make the assessment more accurate.

The data fusion-based approaches have the advantage of outstanding practicality and interpretability because these methods make assessments by weighting the health monitoring indicators to get a health index, and the meaning of indicators are explicit. [13] used information entropy fusion to extract features to analyze the health of turbo-shaft engine gas-path. [14] proposed a mechanical equipment health assessment method based on fuzzy set and analytical hierarchy process (AHP). The weights obtained by AHP are highly interpretable and well-accepted as expert opinion is involved. However, such consequences may be too subjective for the same reason. To reduce the subjectivity of AHP, Niu, et al. [6] proposed a method combined with AHP and the information entropy weight method to evaluate and predict the health status of production lines.The entropy weight method [15] calculates objective weights by considering the difference within each indicator, but the correlation between different indicators is neglected. As a result, when the correlation between each indicator is strong, the entropy weight method does not reflect the information contained in the data well. Besides, most health assessment methods are static, i.e., the weights keep constant once they are determined, and this characteristic may underestimate the impact of the deterioration of a single indicator.

In this paper, a novel assessment method for equipment health status is proposed by combining criteria importance through inter-criteria correlation (CRITIC) [16] and AHP. The correlation between the indicators has been taken into account, solving the limitation of the entropy weight method. In the proposed method, we first use AHP to get the subjective weights, and use CRITIC method to obtain the objective weights. Then by the least square method, the two weights are combined to obtain static weights with both subjective considerations of experts and objective facts in data. In addition, a method of dynamically adjusting the weights is utilized to reflect the actual effect of the deterioration of individual indicators on the overall health of equipment.

The remaining of this paper is organized as follows. Section 2 introduces the proposed assessment method based on AHP-CRITIC dynamic weight. An illustrated example is

This work was supported by the National Natural Science Foundation of China (No. 62173317), and the Key Research and Development Program of Anhui (No. 202104a05020064).

shown in Section 3. In Section 4, a conclusion of this paper is given.

2 The Health Assessment Method Based on AHP-CRITIC Dynamic Weight

In this section, the process of using the assessment method based on AHP-CRITIC dynamic weight is introduced. Specifically, how to construct the evaluation index system and preprocess the raw data are first introduced. We also illustrate the process of obtaining combined weights via AHP and CRITIC. Finally, the dynamic weight adjustment mechanism is added to get the health index of the equipment.

2.1 Construction of evaluation index system

Suppose that there exists m equipment with the same model that needs a health status assessment, with n indicators used to monitor the health status of equipment, such as temperature, humidity, vibration signal, and voltage. All indicators are supposed to be in an ideal working range, and each of them can reflect a particular aspect of health, with its limitation, though. We need to combine indicators with a proper method such that the actual health status of the whole equipment can be reflected accurately.

To describe the health status of different equipment of the same model (the same equipment at a different time is treated as another equipment), we build a health indicators matrix. In the matrix, m columns represent m different equipment, and n rows represent n indicators, respectively. The matrix $\boldsymbol{X}$ is as follow:

$$\boldsymbol{X} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \tag{1}$$

where x_{ij} is the value of the ith monitoring indicator of the jth equipment, $i = 1, 2, ..., n; j = 1, 2, ..., m$.

2.2 Data preprocessing

Monitoring data needs to be preprocessed to bring it into a unified form to assess health status. We convert the monitoring data into a score based on their ideal ranges. Suppose the score for every indicator is between 0 and the total score $\bar{s}$ which is the score of ideal value. The score is $\underline{s}$ when the value is at reference boundary, and satisfy $0 < \underline{s} < \bar{s}$. Indicators can be divided into two kinds. For the first kind, the small the value, the higher the score. The formula of this situation is as follow:

$$s_{ij} = -\frac{\bar{s} - \underline{s}}{\bar{x}_i} x_{ij} + \bar{s} \tag{2}$$

where s_{ij} represents the score of the ith indicator of the jth sample, and $\bar{x}_i$ represents the upper bound of the health range. The second kind of indicators are considered optimal at specific values. The scores are calculated as below:

$$s_{ij} = \begin{cases} \dfrac{(\bar{s} - \underline{s})}{x_i^* - \bar{x}_i}(x_{ij} - x_i^*) + \bar{s}, & x_{ij} < x_i^* \\ \dfrac{(\bar{s} - \underline{s})}{x_i^* - \underline{x}_i}(x_{ij} - x_i^*) + \bar{s}, & x_{ij} \geq x_i^* \end{cases} \tag{3}$$

where $\underline{x}_i$ represents the lower bound of the health range, and x_i^* represents the ideal value of the ith indicator.

After the scoring process (2) and (3), we obtain a scoring matrix $\boldsymbol{S}$.

$$\boldsymbol{S} = \begin{bmatrix} s_{11} & s_{12} & \cdots & s_{1m} \\ s_{21} & s_{22} & \cdots & s_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ s_{n1} & s_{n2} & \cdots & s_{nm} \end{bmatrix} \tag{4}$$

where s_{ij} is the score of x_{ij}, $i = 1, 2, ..., n; j = 1, 2, ..., m$.

2.3 Subjective weights calculation: AHP

AHP is a multi-objective decision analysis method that combines qualitative and quantitative analysis techniques and is one of subjective weighting methods, based on mathematics and psychology [17–19]. This technique simplifies the complex decision problem by breaking it down into several levels and factors. Moreover, AHP can calculate the consistency of the evaluation procedure to determine if it's appropriate. The steps of AHP are as below:

1) Make the problem hierarchical and determine which indicators will use.
2) Compare each indicator pairwise and establish the judgment matrix called $\boldsymbol{J}$ by a measurement scale presented in Table 1.
3) Solve $\boldsymbol{J}\boldsymbol{\alpha} = \lambda\boldsymbol{\alpha}$ to obtain the maximum eigenvalue $\bar{\lambda}$ and the corresponding eigenvector $\bar{\boldsymbol{\alpha}}$.
4) Calculate the consistency index CR according to (5) to check consistency of $\boldsymbol{J}$. If $CR < 0.1$, $\boldsymbol{J}$ passes the consistency check.

$$CR = \frac{CI}{RI} \tag{5}$$

where

$$CI = \frac{\bar{\lambda} - n}{n - 1} \tag{6}$$

and RI represents the random index that varies for different matrix dimensions, and the values are shown in Table 2.

5) The eigenvector $\bar{\boldsymbol{\alpha}}$ needs to be normalized to make sure they can use as weights. The calculation is as below:

$$\omega_{ai} = \frac{\alpha_i}{\sum_{i=1}^{n} \alpha_i} \tag{7}$$

where ω_{ai} is the weight of ith indicator calculated by AHP, α_i is the ith element of $\bar{\boldsymbol{\alpha}}$, $i = 1, 2, ..., n$. Denote the weight vector as $\boldsymbol{\omega_a} = [\omega_{a1}, \omega_{a2}, ..., \omega_{an}]^T$. Unless otherwise specified, every vector in this paper is a column vector.

2.4 Objective weights calculation: CRITIC

The CRITIC method aims to determine objective weights of relative importance in Multi-Criteria Decision-Making (MCDM) problem. There are another two different methods of determining objective weights in the MCDM problem: standard deviation weight method [20] and information entropy weight method [15]. They calculate weights by

Table 1: Measurement scale used by AHP

Intensity of preference important	Meaning (A compared to B)
1	A is equally important /preferred to B
3	A is moderately more important/preferred than B
5	A is strongly more important/preferred than B
7	A is very strongly more important/preferred than B
9	A is extremely more important/preferred than B
$2, 4, 6, 8$	The intermediate value of the above adjacent judgments
The reciprocal of $1, 2, ..., 9$	The degree to which B is more important/preferred than A

Table 2: Values of RI for different dimensions

Order	1	2	3	4	5	6	7	8	9	10	...
RI	0	0	0.58	0.89	1.12	1.26	1.36	1.41	1.45	1.49	...

considering the information within the same single indicator. But when the indicators are coupled, these two methods do poorly. Unlike them, the CRITIC method considers the correlation between indicators, overcoming this shortcoming. In this method, objective weights are determined comprehensively by both contrast intensity under each indicator and correlation in the structure of the decision problem. The contrast intensity represents the difference between the values under the same indicator, reflected by the standard deviation. A larger standard deviation means more information under this indicator, giving a larger weight. The correlation is measured by the correlation coefficient between two indicators. The larger the correlation coefficient, the larger the similarity of information reflected by them, and the smaller the weights.

The typical calculation process of CRITIC is as below:

1) Compute the scores as below to make sure they are in a normalized form:

$$a_{ij} = \frac{s_{ij} - \underline{s}_i}{\bar{s}_i - \underline{s}_i} \tag{8}$$

where $\bar{s}_i$ and $\underline{s}_i$ represent the maximum and the minimum score of the ith indicator, respectively. Then a normalized score matrix $\boldsymbol{A}$ is obtained:

$$\boldsymbol{A} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nm} \end{bmatrix} \tag{9}$$

2) Consider the vectors generated by each indicator separately, and calculate the standard deviation σ_i of each row vector A_i. The formula of standard deviation is as below:

$$\sigma_i = \sqrt{\frac{\sum\limits_{i=1}^{n}(a_{ij} - E(a_i))^2}{n-1}} \tag{10}$$

where $E(a_i)$ is the mathematical expectation of $a_{ij}, j = 1, 2, ..., m$.

3) Calculate the correlation coefficient r_{ik} which is of ith and kth indicator as below:

$$r_{ik} = \frac{\sum\limits_{j=1}^{m}(a_{ij} - E(a_i))(a_{kj} - E(a_k))}{\sqrt{\sum\limits_{j=1}^{m}(a_{ij} - E(a_i))^2}\sqrt{\sum\limits_{j=1}^{m}(a_{kj} - E(a_k))^2}} \tag{11}$$

where $i, k = 1, 2, ..., n$. Denote the correlation coefficient matrix as $\mathbf{R} = (r_{ik})_{n\times n}$.

4) Calculate the amount of information c_i of the ith indicator as follow:

$$c_i = \sigma_i \sum_{k=1}^{n}(1 - r_{ik}) \tag{12}$$

Form c_i into a vector of the amount of information $\boldsymbol{c}$.

5) The vector of the amount of information $\boldsymbol{c}$ needs to be normalized. The normalization process is as below:

$$\omega_{ci} = \frac{c_i}{\sum\limits_{i=1}^{n} c_i} \tag{13}$$

where ω_{ci} is the weight of ith indicator calculated by CRITIC, $i = 1, 2, ..., n$. Denote the weight vector as $\boldsymbol{\omega_c} = [\omega_{c1}, \omega_{c2}, ..., \omega_{cn}]^T$.

2.5 AHP-CRITIC combined weight

After the calculation of AHP and CRITIC, we get a subjective weight vector $\boldsymbol{\omega_a}$ and an objective one $\boldsymbol{\omega_c}$. A method is needed to combine the weights of AHP and CRITIC. We use the least square method to calculate the combined static weight $\boldsymbol{\omega_s}$, as follows:

$$\begin{cases} \min\limits_{\boldsymbol{\omega_s}} \sum\limits_{i=1}^{n}[(\omega_{si} - \omega_{ai})^2 + (\omega_{si} - \omega_{ci})^2] \\ \text{s.t.} \sum\limits_{i=1}^{n}\omega_{si} = 1, \omega_{si} \geq 0, j = 1, 2, ..., n \end{cases} \tag{14}$$

where ω_{si} represents the ith element of the static weight vector $\boldsymbol{\omega_s}$ combined by $\boldsymbol{\omega_a}$ and $\boldsymbol{\omega_c}$.

2.6 Dynamic weight mechanism

In the conventional health status assessment method, the weight of each indicator always keep constant after being determined. Suppose the value of some indicator is beyond the normal range. In that case, it is possible that the health index still indicates that the equipment works fine because the weight of this indicator is relatively small. This situation shows that static weighting methods have their inherent disadvantages. The weight of an indicator needs to increase as it deteriorates. Consequently, a dynamic weight mechanism is proposed in this paper to avoid abnormal conditions being ignored. In general, the risk of failure multiplies with the deviation of indicators. Thus, the dynamic weight should also multiply to assess the actual health status, which is precisely the nature of exponential functions. We use an exponential function as below to adjust weight:

$$\omega_{di} = \mu_i^{\delta_i}\omega_{si} \tag{15}$$

where ω_{di} represents the dynamic weight of ith indicator, and μ_i represents the base number of the ith indicator, and

$$\delta_i = \frac{|x_i - x_{i0}|}{\bar{x}_i - \underline{x}_i} \tag{16}$$

where $\bar{x}_i$, $\underline{x}_i$, and x_{i0} represent the maximum reference value, the minimum one and the ideal one, of the ith indicator, respectively.

At last, the weights ω_{di} need to be normalized. The normalization process is as below:

$$\omega_i = \frac{\omega_{di}}{\sum_{i=1}^{n} \omega_{di}} \tag{17}$$

where ω_{di} is the weight of ith indicator obtained in (15), $i = 1, 2, ..., n$. Let $\boldsymbol{\omega} = [\omega_1, \omega_2, ..., \omega_n]^T$.

The result $\boldsymbol{\omega}$ is the final weight vector of the indicators used to assess the health index H of equipment. Suppose that the score vector of an equipment is $\mathbf{s}$, the calculation of H is as below:

$$H = \boldsymbol{\omega}^T \cdot \mathbf{s}$$

3 Case Study

Surface mount technology (SMT) is a critical technology in the electronics industry, and a chip mounter is a key equipment in the SMT production line system. The primary function of a chip mounter, mounting the chip to the printed circuit board (PCB), is implemented by its suction nozzles. Most of the SMT production line failures come from the suction nozzles of chip mounters, which significantly affect production efficiency and product quality. Therefore, ensuring the health of the chip mounter suction nozzle is of great significance to ensure the normal production of the SMT production line and good product quality.

We use the monitoring data of different suction nozzles of a chip mounter in a laptop factory to do an case study. We select 11 suction nozzles of the same model. More than 20 indicators are used to monitor the working condition of suction nozzles of a specific type of chip mounter, including some being less referential. Combining expert experience with data, we exclude indicators that are not critical to health status, and six indicators are selected, as shown in Table 4. These representative and measurable indicators can build a health assessment index system.

Suppose that the total score of the health index $\bar{s} = 100$, and the score of the boundary score $\underline{s} = 60$, then the health index can take the value between 0 to 100. Different score segments are divided into different health levels according to expert experience, and the relationship is shown in Table 3.

The essential data of the monitoring indicators of different suction nozzles of this chip mounter is shown in Table 4, including the raw data , the ideal value vector $\boldsymbol{x}^*$, the maximum reference value vector $\bar{\boldsymbol{x}}$, the minimum reference value vector $\underline{\boldsymbol{x}}$, and the base number vector $\boldsymbol{\mu}$. Bold numbers represent values outside the reference range.

The experiment is carried out in Windows10 and MATLAB environments. The weights calculated by AHP, CRITIC, and the combined static one are shown in Table 5.

The health index is the weighted average of the scores (4). To make a comparison, we use the weights $\boldsymbol{\omega_a}$, $\boldsymbol{\omega_c}$, $\boldsymbol{\omega_s}$, and

Table 3: Health levels of the health assessment

Serial numbers	Health Level	Range of Health Index	Description
I	Perfect Health	$[85, 100]$	The equipment is in perfect health and safety
II	Health	$[70, 85)$	The equipment is in good health and safety
III	Sub-health	$[60, 70)$	The equipment is not safe, with slight signs of failure and the requirement of better monitoring
IV	Failure	$[40, 60)$	The equipment is very unsafe with severe signs of failure and requires soon repair
V	Complete failure	$[0, 40)$	The equipment is entirely out of order and requires immediate repair

$\boldsymbol{\omega}$ obtained in (7), (13), (14), and (17), respectively to calculate the final health indexes of the suction nozzles. Besides, H_e represents the health indexes given by experts. The results are shown in Fig. 1.

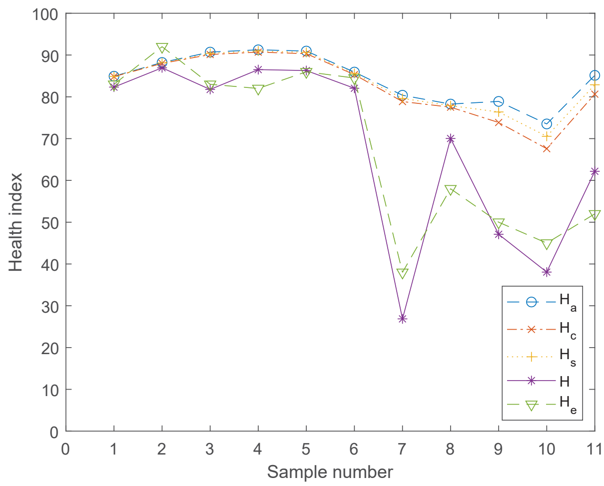

Fig. 1: Health indexes get from different way

In general, the indexes obtained by the dynamic weight method are closer to experts' opinions. It can be seen that the health indexes calculated by $\boldsymbol{\omega_a}$, $\boldsymbol{\omega_c}$ and $\boldsymbol{\omega_s}$ are close. This phenomenon means that the weights get by AHP and CRITIC, respectively, are consistent with each other to a certain extent. However, the static weight method gives some suction nozzles scores of more than 80, even with some indicators being out of the reference range, e.g., sample 11.

As a comparison, the health index calculated by the dynamic weight $\boldsymbol{\omega}$ can reflect the health status more accurately. As we can see, samples 1 to sample 6, whose indicators are within the reference range, all get indexes over 80. But sample 1, sample 3, and sample 6 have some indicators approaching but not going beyond the reference range boundary, so their indexes are below 85, and their health level is "Health" rather than "Perfect health". The situation that these indexed below 85 is a reminder to engineers, not re-

Table 4: Important data of chip mounter suction nozzles

Indicators\Serial numbers	1	2	3	4	5	6	7	8	9	10	11	x^*	$\bar{x}$	$\underline{x}$	μ
Blow on leakage	14	14	14	14	14	14	13	17	**22**	**24**	**22**	12.5	20	5	35
Vacuum on leakage	-23	-24	-20	-21	-22	-26	-23	**-33**	**-41**	**-41**	**-35**	-18.5	-5	-32	80
Vacuum on blockage	-90	-92	-89	-90	-90	-90	**-87**	-90	-89	**-84**	-92	-94	-88	-100	100
Blow valve on delay	11	10	9	10	10	10	9	7	8	9	9	9.5	13	6	30
Blow valve off delay	8	7	7	7	7	8	7	5	7	9	8	7.5	11	4	40
Vacuum on delay	4	7	6	5	5	7	7	6	5	5	5	5.5	9	2	35

Table 5: Weights calculated by different methods

Indicators	$\boldsymbol{\omega_a}$	$\boldsymbol{\omega_c}$	$\boldsymbol{\omega_s}$
Blow on leakage	0.085	0.156	0.120
Vacuum on leakage	0.101	0.130	0.115
Vacuum on blockage	0.127	0.144	0.136
Blow valve on delay	0.165	0.142	0.154
Blow valve off delay	0.186	0.126	0.156
Vacuum on delay	0.335	0.305	0.320

flected in the static weight method.

In addition, the assessment method with dynamic weighting mechanism has more advantages than the static one. The samples with indicators out of the reference range have lower indexes, obviously. For example, sample 10 has three indicators out of the ideal range, and the health index of this sample is 38.1, notifying everyone that this sample is in failure condition.

The assessment on sample 9 is an excellent example of the gap between the weighting methods with and without the dynamic adjustment mechanism. As the indicator "Vacuum on blockage" of sample 9 is far from the reference range, it is actually in a failure condition. However, the assessment result given by the AHP-CRITIC weighting method without the dynamic adjustment mechanism is "Health", being very different from the actual situation. On the contrary, the dynamic weighting method reflects the actual health status, giving sample 9 a health index of 26.86. The health index H changes linearly in the static method, so the influence of the extreme situation that single indicator deteriorate seriously is limited. This shortcoming is remedied due to the nonlinear of the dynamic weighting method. In this case, the dynamic weight method gives out an appropriate assessment. To sum up, it is crucial to adjust the weights dynamically in health assessment, and the method proposed in this paper is referential.

4 Conclusions

An assessment method based on AHP-CRITIC dynamic weight for equipment health status is proposed in this paper. The AHP and CRITIC methods are combined to obtain weights, including opinions of experts and the information of data. After that, a dynamic weight adjustment mechanism is utilized to highlight the effects of indicators that deviate far from the ideal range. The case study for suction nozzles shows the effectiveness and superiority of the proposed method.

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