Assessment Method for Equipment Health Status Based on AHP-CRITIC Joint Dynamic Weight

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Abstract: With the improvement of different equipment, Prognostics Health Management(PHM) has become a hot research problem. Besides, it is significant to assess the health status of equipment in PHM. Existing evaluation methods do not reflect the true health status of equipment well. To reflect equipment health status more accurately, a method of AHP-CRITIC joint weight is proposed in this paper. Analytic Hierarchy Process(AHP) is a subjective method used to evaluate the importance of different factors. The CRITIC method is used to calculate the contrast strength of the same indicator and the conflict between indicators, and obtain the objective weight of the indicators. A more scientific weight is gained by combining the weights obtained from AHP and CRITIC respectively. Moreover, in order to reflect the real impact of each indicator on overall health status, a dynamic weight adjustment method is proposed. The actual test of the head of a certain type of chip mounter shows that this method can reflect the health status accurately and truthfully to a certain extent.

Key Words: PHM, Equipment health status, AHP-CRITIC joint weight, Dynamic weight

1 Introduction

Prognostics Health Management(PHM) aims to provide an integrated framework for degradation prediction and maintenance policies to mechanical and electrical equipment[1]. The health status of equipment can be defined as the ability of equipment to maintain a certain level of reliability and maintainability and to perform its intended functions stably and continuously under specified conditions and within a specified period of time[2]. Accurate methods for equipment health status assessment are instructive for degradation prediction. In fact, health status is inherited from the medical field, so that engineering staff can describe working status of systems between normal and failure, instead of just relying on these two states as people used to do in the past.

In general, there are two different ways in equipment health status assessment, 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 inconsistent classification and inaccuracy in the former, using a numerical value to assess health status is preferred in the current study. A variety of different kinds of health assessment approaches have been proposed in these years, which can be divided roughly into four categories. The first one is data fusion, integrating various monitoring data to determine equipment health level[3–6]. Due to the fuzziness of the health status, many approaches assess health status by using fuzzy theory methods[7, 8]. Moreover, as the advances in Machine Learning(ML), many ML techniques have been utilized to evaluate the health status of equipment, such as SVDD[9], SVM[10] and Deep Learning[11], etc. Because of the complexity of modern equipment and systems, some hybrid methods have been proposed[2, 12].

Surface Mount Technology(SMT) is a key technology in the electronics industry, and chip mounts are key equipment in SMT production line system. The main function of a chip mount, mounting the chip to the Printed Circuit Board(PCB), is implement by its head. Most of the failures on the SMT production line come from the head of chip mount, and these failures greatly affect the efficiency and product quality of production. However, existing method of chip mounter health monitoring can only monitor some running indicators respectively, and detect if they are out of the normal range. Therefore, it is meaningful to proposed an approach to combine these indicators to reflect the actual health status of the chip mounter head.

For this reason, the CRITIC method is utilized to mining objective information of running indicators and to determine the objective weight of each indicator. Then combine the subjective weights determined by AHP. By doing this, the approach proposed in this paper combines the subjective considerations of experts with the objective facts of the data. In addition, to reflect the actual effect of deterioration of individual indicators on the overall health of equipment, a method of dynamically adjusting the weights is proposed. At last, an assessment method for equipment health status based on AHP-CRITIC joint dynamic weight is proposed, which can relatively accurately reflect the actual health of equipment.

The remaining of this paper is organized as follows. Section 2 introduces the principles of AHP, CRITIC and dynamic weight adjustment approach, and how to combine them into a whole. An illustrate example is given in Section 3.In Section 4, we make a conclusion, and an outlook on future research directions.

2 The principle and calculation method of the joint dynamic weight

2.1 Construction of evaluation index system

Due to the precision of the chip mounter head, many indicators are used to evaluate the health status of it. However, a single indicator can only reflect the state of a single aspect,

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with its own limitation. Therefore, we consider to combining these indicators with a proper approach, so that the actual health status of the whole equipment can be reflected accurately.

More than 20 parameters are used to monitor the working condition of the head of a certain type of chip mounter, including some that are less referential. Combining expert experience with data, we exclude indicators which are not critical to health status, and the following indicators were selected:(). These representative and measurable indicators can build a health assessment index system.

To describe the health status of different chip mounter heads, we build a health indicators matrix, which has m columns to represent m different running states of chip mounter heads, and n rows to represent n indicators. The matrix H_{mn} is as follow

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

where x_{ij} is the value of the ith indicator of the j chip mounter head $(i = 1, 2, ..., n; j = 1, 2, ..., m)$.

2.2 Data preprocessing

To assess health status, data needs to be preprocessed to bring it into standard form. We convert the monitored data into a score based on the values of the data and their ideal ranges. Some indicators indicate good equipment when they are in a range, while others are better as large or as small as possible. So that we have different standardized formulas for these different kinds of data as follows.

(2)

After the standardization process2, H_{mn} becomes the following form.

$$H_{mn} = \begin{bmatrix} \alpha_{11} & \alpha_{12} & \cdots & \alpha_{1m} \\ \alpha_{21} & \alpha_{22} & \cdots & \alpha_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \alpha_{n1} & \alpha_{n2} & \cdots & \alpha_{nm} \end{bmatrix} \tag{3}$$

α_{ij} is the standardized value of x_{ij}, which is between 0 and 1. $(i = 1, 2, ..., n; j = 1, 2, ..., m)$.

2.3 Subjective weight calculation: AHP

AHP[13] is a multi-objective decision analysis method that combines qualitative and quantitative analysis methods, and is a kind of subjective weighting approach. This technique simplifies the complex decision problem by breaking it down into several levels and factors. And AHP has the ability to calculate the consistency of the evaluation procedure to determine if it's appropriate. The steps of AHP are as below[14]:

1) Make the problem hierarchical, determine which indicators will be used.
2) Compare each indicator pairwise and establish the judgment matrix called J, by a measurement scale presented in table1.
3) Solve $J\alpha = \lambda\alpha$ yields maximum eigenvalue λ_{max} and the corresponding eigenvector α_{max}.
4) Calculate the consistency index CR, which is calculate as 4 to check consistency of J. If $CR < 0.1$, J passes the consistency check.

$$CR = \frac{CI}{RI} \tag{4}$$

where

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{5}$$

and RI represents the random index that varies for different matrix dimension, the value is showed in table2. Besides, n represents the order of J.

5) The eigenvector α_{max} need to be normalized to make sure they can be used as weights. The calculation is as below:

$$\omega_i = \frac{\alpha_i}{\sum_{i=1}^{n} \alpha_i} \tag{6}$$

where α_i is the ith element of α_{max}, $i = 1, 2, ..., n$

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: Random index of one pairwise comparison matrix

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	...

2.4 Objective weight calculation: CRITIC

The method CRITIC (Criteria Importance Through Intercriteria Correlation)[15] aims at the determination of objective weights of relative importance in Multi-Criteria Decision-Making(MCDM) problem. In this method, the objective weights are determined comprehensively by both contrast intensity in each indicator and conflict in the structure of the decision problem. The contrast intensity represents the difference between the values of the same indicator, which is reflected by the standard deviation. A larger standard deviation means more information in this indicator, which will be given a larger weight. The conflict is measured by the correlation coefficient between two indicators. The lager the correlation coefficient, the smaller the similarity of information reflected by them, and the larger the weights. There are two different methods of determining objective weights in MCDM problem.

2.5 Dynamic weight mechanism

2.6 Joint weight calculation

3 Numerical Example

4 Conclusions

References

[1] T. Xia, Y. Dong, L. Xiao, S. Du, E. Pan, and L. Xi, "Recent advances in prognostics and health management for advanced manufacturing paradigms," *Reliability Engineering & System Safety*, vol. 178, pp. 255–268, 2018.

[2] B. Liu, H. Wang, W. Fan, T. Xiao, D. O. Automation, and T. University, "Real-time health level assessment for complex production line system based on big data," *Journal of Tsinghua University*, vol. 54, no. 10, pp. 1377–1383, 2014.

[3] J. Lv, P. Yu, J. Wei, and J.-j. YANG, "Assessment method of health conditions of naval vessel system," *J Naval Univ Eng*, vol. 23, no. 3, pp. 72–76, 2011.

[4] J. She, W. Yao, J. Shi, X. Zhuo, and J. Li, "Multi-dimensional health evaluation of equipment in electric power communication network," in *2019 IEEE 3rd Advanced Information Management, Communicates, Electronic and Automation Control Conference (IMCEC)*, pp. 40–43, IEEE, 2019.

[5] L. Zhao, C. Liu, and F. Yi, "Assessment method of equipment health state based on dynamic weight," *Computer Systems & Applications*, vol. 29, no. 9, pp. 198–204, 2001.

[6] G. Niu, Z. Hu, and D. Hu, "Evaluation and prediction of production line health index based on matter element information entropy," *Computer Integrated Manufacturing Systems*, vol. 25, no. 7, pp. 1639–1646, 2019.

[7] Z. Cao and J. Shen, "Sensor health degree evaluation method based on fuzzy set theory," *Electric Machines and Control*, vol. 14, no. 5, pp. 79–90, 2010.

[8] S. Liu, "A comprehensive evaluation study on the health status of multi-feature parameters of mechanical equipment based on fuzzy hierarchical analysis," in *2018 International Conference on Sensing, Diagnostics, Prognostics, and Control (SDPC)*, pp. 621–625, IEEE, 2018.

[9] L. Zhang, F. Qiao, J. Wang, and X. Zhai, "Equipment health assessment based on improved incremental support vector data description," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 51, no. 5, pp. 3205–3216, 2019.

[10] C. Zhang and M. Shu, "Health assessment method based on support vector machine," *Computer Systems & Applications*, vol. 27, no. 3, pp. 18–26, 2018.

[11] A. W. Techane, Y.-F. Wang, and B. H. Weldegiorgis, "Rotating machinery prognostics and application of machine learning algorithms: Use of deep learning with similarity index measure for health status prediction," in *Proceedings of the Annual Conference of the Prognostics and Health Management Society, Philadelphia, PA, USA*, vol. 24, 2018.

[12] Y. PENG, W. LI, J. LIU, and Q. CHEN, "Health assessment model based on dynamic weight and fuzzy comprehensive evaluation method," *Computer Systems & Applications*, vol. 26, no. 1, pp. 37–43, 2017.

[13] S. TL, "The analytic hierarchy process, planning, priority setting," *Resource Allocation*, 1982.

[14] D. Sedghiyan, A. Ashouri, N. Maftouni, Q. Xiong, E. Rezaee, and S. Sadeghi, "Prioritization of renewable energy resources in five climate zones in iran using ahp, hybrid ahp-topsis and ahp-saw methods," *Sustainable Energy Technologies and Assessments*, vol. 44, p. 101045, 2021.

[15] D. Diakoulaki, G. Mavrotas, and L. Papayannakis, "Determining objective weights in multiple criteria problems: The critic method," *Computers & Operations Research*, vol. 22, no. 7, pp. 763–770, 1995.