International Journal of u- and e- Service, Science and Technology
Vol.8, No. 9 (2015), pp.207-216
http://dx.doi.org/10.14257/ijunesst.2015.8.9.22

Extension Model of Fault Diagnosis for Complex Mechanical Equipment and Its Application

Zefeng Zheng

Agricultural University of Hebei; Baoding, Hebei 071001, China
E-mail: 332443459@qq.com

Abstract

Based on the diversity, complexity and uncertainty of the fault information of complex mechanical equipment, this paper conducts extension analysis about the failure diagnosis for complex mechanical equipment and provides the extension model. This model carries out knowledge modeling about the failure diagnosis information based on matter element model, acquires the weight of different kinds of fault by grey correlation analysis, and establishes extensible dependence between different features of failure diagnosis according to extension data. Analysis of different fault information is conducted by identifying the type of faults based on extensible dependence. At last, the model and algorithm are testified through design examples.

Keywords: *complex product, Fault Diagnosis, Complex Mechanical Equipment, Extension Theory, Artificial Intelligence, Model*

1. Introduction

Failure of the mechanical equipment refers to the abnormal condition of the equipment when its function is partly or totally lost. The failure will lead to the change of the output state and may even cause industrial accident and endanger life safety of operation staff. The equipment failure contains various changes of failure information, so it is of great analysis value and application value to study the methods to acquire typical information and apply it to failure diagnosis. Currently, there are mainly three kinds of methods for failure diagnosis: (1) method based on signal processing [1-3]; (2) method based on analytical model [4-6]; (3) knowledge-based diagnosis [7-10].

However, these traditional methods are ambiguous and uncertain, unable to provide more accurate failure diagnosis model for the faults with smaller sample and little information. Extenics analyzes the possibility of extension as well as rules and solutions of contradictory problems by using formal model, which is mathematized, logicalized and formalized. The failure diagnosis based on extension theory means to combine failure diagnosis with extension theory according to certain programs and algorithms and to set up models to find the cause of equipment faults. It is meaningful both theoretically and practically to conduct research on the application of this new method in order to enhance the intelligence, efficiency and accuracy of failure diagnosis.

2. Failure Diagnosis of Complex Mechanical Equipment based on Extension Model

2.1 Matter Element Modeling of Equipment Failure Information

Extenics is an interdisciplinary subject established by Chinese scholar Professor Cai Wen. It expresses design object by formalized knowledge modeling, studies the

ISSN: 2005-4246 IJUNESST

possibility and feasibility of the extension of the object and discusses general patterns and methods of extension creativity. Matter element is one of the logical cells of extension theory, which is used to establish the extension model, a formal tool that can solve design problems and knowledge modeling [15-16]. Failure information of mechanical equipment has different characteristics and the corresponding characteristic value, so the establishment of failure information model is the formal description of such characteristics and characteristic value.

Matter element uses an ordered triple $R=(O,c,v)$ as the basic element to describe failure information. O Represents the name of the fault, c refers to the characteristics of the fault while v stands for the measurement value of O on c. One fault may have several characteristics, and if we use n-kinds of characteristics $c_1,c_2,\cdots c_n$ and their corresponding value $v_1,v_2,\cdots v_n$ to describe the fault O, then the corresponding matter element model will form a matrix array with n-sphere matter elements as follows:

$$R=(O,C,V)=\begin{bmatrix} O & c_1 & v_1 \\ & c_2 & v_2 \\ & \vdots & \vdots \\ & c_n & v_n \end{bmatrix} \tag{1}$$

In the formula, $C=(c_1,c_2,\cdots,c_n)^T$, $V=(v_1,v_2,\cdots,v_n)^T$.

During the process of failure analysis, different types of failure information will be described by matter element and the corresponding information element will be generated, providing the formal tool for the implementation of computer intelligence for product design.

The selection of evaluation indexes of assimilability of complex product assembling scheme is based on the assembling features of the components and parts themselves and the features of generative process of assembling scheme. The former considers mainly about the effects characteristic parameters of components have on the assembling features. The latter focuses on the effects the assembling path and crafting have on the product assembling features from the perspective at scheme level.

2.2 Establishing Extension Model for Failure Diagnosis

The establishment of the mechanical equipment failure diagnosis model is the basis of failure diagnosis. With the theoretical development of failure diagnosis, especially the improvement and application of expert system theory, failure diagnosis techniques with information processing as the core have developed in the direction of intelligent diagnosis based on knowledge. But expert diagnosis system relies on the knowledge of experts, and has limitations in adaptation ability, learning ability as well as timeliness.

The establishment of failure diagnosis model based on extension theory makes use of the matter element theory and contributes to a formal expression of the failure model. It is not only simple, normative, logical and easy to operate, but also overcomes the limitation of knowledge scope. General failure model based on extension theory is as follows:

$$RX_i=\begin{bmatrix} RI_i & c_1 & \mathrm{v}x_i(1) \\ & c_2 & \mathrm{v}x_i(2) \\ & \vdots & \vdots \\ & c_n & \mathrm{v}x_i(n) \end{bmatrix} \quad i=1,2,\cdots,m \tag{2}$$

In the formula, RX refers to equipment object, RI refers to failure mode, and m stands for the number of failure modes. C means the characteristics of the faults, n means the number of characteristics of the ith failure mode in RI system, and vxi(j) means the characteristic value of the jth characteristics.

Due to the measuring error of the equipment and the uncertainty of other factors, the characteristic value of the failure is usually an interval. Thus, the foregoing characteristic value can be altered as characteristic interval, and the standard failure model is as follows:

$$RX_i = \begin{bmatrix} RI_i & c_1 & \left(vx_{i-\min}(1), vx_{i-\min}(1)\right) \\ & c_2 & \left(vx_{i-\min}(2), vx_{i-\min}(2)\right) \\ & \vdots & \vdots \\ & c_n & \left(vx_{i-\min}(n), vx_{i-\min}(n)\right) \end{bmatrix} \quad i = 1,2,\cdots m \tag{3}$$

In the formula, $VX_i(j) = \left(vx_{i-\min}(j), vx_{i-\min}(j)\right)$ means the characteristic interval of the jth characteristics.

$$RX_0 = \begin{bmatrix} RI_0 & c_1 & \mathrm{v}x_0(1) \\ & c_2 & \mathrm{v}x_0(2) \\ & \vdots & \vdots \\ & c_n & \mathrm{v}x_0(n) \end{bmatrix} \tag{4}$$

Failure diagnosis requires comparative analysis between the data measured and the standard failure model in order to find the closest standard failure model and make judgment about the equipment failure. Therefore the modeling of the acquired data is needed as well. It is shown as follows:

$$RX_0 = \begin{bmatrix} RI_0 & c_1 & \mathrm{v}x_0(1) \\ & c_2 & \mathrm{v}x_0(2) \\ & \vdots & \vdots \\ & c_n & \mathrm{v}x_0(n) \end{bmatrix} \tag{4}$$

RI0 represents the failure modes waiting to be diagnosed, and vx0(j) refers to the failure data which can either be the specific failure value or the failure interval.

2.3 Analysis of Weight of Failure Characteristics

Weight represents the significance level of failure characteristics. The more complicated the model is, the more characteristic value it has, and the weight of each characteristic varies. Failure diagnosis is related with a large number of characteristic data, therefore the weight of each characteristic is influential in the final result. The more accurate, scientific and objective the weight is, the closer the result is to the real fact, and the more convincing and practical the outcome is. Grey correlation analysis makes up the disadvantage of traditional mathematical statistics and can conduct systematic analysis with small sample, little information and no regular patterns, whose result is close to qualitative analysis. Grey correlation analysis uses the degree of similarity to judge the correlation degree. The closer the curves are, the more correlation they have, and vice versa.

The analysis on a failure system or model can select characteristic values that can reflect the model's features as data. If the kth characteristic of failure model Xi is written as xi(k), then there is the sequence:

Xi=(xi(1) , xi(2) , xi(3) ,… ,xi(k))k=1,2,3…,n,

The data being measured or compared can be written as:

X0=(x0(1) , x0(2) , x0(3) ,… ,x0(k))k=1,2,3…,n.

The system analysis requires the correlation degree between the data measured and the standard data. The formula to calculate the correlation coefficient ξ of the index point k is as follows:

$$\xi_i(k)=\frac{\min_i\min_k\left|x_0(k)-X_i(k)\right|+\beta\max_i\max_k\left|x_0(k)-X_i(k)\right|}{\left|x_0(k)-X_i(k)\right|+\beta\max_i\max_k\left|x_0(k)-X_i(k)\right|}\quad \beta\in(0,1),\quad k=1,2,\cdots n \tag{5}$$

After calculating the correlation degree of all the equipment failure characteristics and the normalization of the data, the weight of each characteristic w can be obtained.

2.4 Calculation of Failure Correlation based on Extension Theory

The extension theory provides an effective tool to evaluate the current state. Its feature is to establish matter element model with multiple indicators by using correlation function based on matter-element characteristics. In order to describe the degree of a certain quality, Extenics defines "distance" to express the distance between the point and the interval.

If x is the failure data measured, and the interval X0=<a,b> represents the type of failure, then

$$\rho(x,X)=\left|x-\frac{a+b}{2}\right|-\frac{a-b}{2} \tag{6}$$

is the distance between x and X0. <a,b> can either be open or closed interval, or half closed interval.

From this we can know that no matter the measured data lie within the interval or not, the correlation degree between the measured data and standard failure model can be reflected.

After the calculation of "distance" between measured data and the characteristic value of a certain failure model, the sequence of "distance" is obtained as $\rho_i = (\rho(1),\ \rho(2),\ \cdots,\ \rho(n))$, and the initialization of "distance" is as follows:

$$\rho_i = (\rho(1)d_1,\ \rho(2)d_1,\ \cdots,\ \rho(n)d_1) \tag{7}$$

In the formula, $\rho(i)d_1=\rho(i)/\rho(1)$,ρ (1)≠0,i=1,2,…,n. Initialization is to compare the sequential value of each "distance" with the first value so that they can be put in the same formula after the nondimensionalization.

Apply the concept of "distance" to the formula of grey correlation coefficient and then the improved formula of extensive correlation coefficient can be obtained:

$$\gamma_{0i}(k)=\frac{\min_i\min_k\rho(x_0(k),\ X_i(k))+\beta\max_i\max_k\rho(x_0(k),\ X_i(k))}{\rho(x_0(k),\ X_i(k))+\beta\max_i\max_k\rho(x_0(k),\ X_i(k))} \tag{8}$$

In the formula, $\beta\in(0,1)$, k = 1 , 2 , 3 ,…,n , i = 1 , 2 , 3 , … , m

The correlation coefficient between the characteristic data of the failure to be detected and the standard failure model can be drawn from the formula above. Considering the weight of different indicators, the correlation coefficient is calculated as follows:

$$\gamma_{0i}=\sum_{k=1}^{n}w_k\gamma_{0i}(k)\quad i=1,2,\cdots m \tag{9}$$

The type of failure can be judged according to the correlation coefficient. The higher the correlation coefficient is, the closer the failure to be detected is to the corresponding standard failure model, leading to the judgment of the type of the equipment failure. If the correlation coefficient between the data to be tested and the two standard failure models are much higher than other coefficient, then it can be considered that more than one fault occur to the equipment.

2.5 Extension Algorithm Implementation for Failure Diagnosis

After failure modeling, it is required to conduct comparative analysis between data of the failure model acquired in the real situation and the standard failure model data. After the correlation coefficient between the two, the diagnosis of the failure model of the mechanical equipment can be drawn.

The specific diagnosis steps are as follows:

1) Identify failure model RX0 that is to be detected and all standard failure model RXi(i=1, 2 ,3,…,m) based on formula (1)-(4).

2) Decide the weight of each characteristic according to formula (5).

3) Calculate the distance between characteristic value of the model to be detected and the standard model by formula (6).

4) Use formula (7) to standardize the failure distance to obtain dimensionless sequences.

5) Use formula (8) to acquire the formula of correlation coefficient between data to be detected and the standard failure model, and then calculate the correlation coefficient according to the formula.

6) Based on formula (9), multiply each correlation coefficient by its weight, and the correlation degree between the failure to be detected and standard failure model can be obtained.

7) Identify the failure model. The correlation degree reflects the closeness of the unknown failure and a certain kind of failure. After the six steps above, the correlation degree can be obtained. According to the principle of maximum correlation, list them in the descending order, and the model with highest correlation is the failure model. In next chapter, the failure diagnosis of transformers is presented to show the feasibility and practicability of this method.

3. Application Case

Failure diagnosis of a transformer is shown in this paper to further illustrate this method. Dissolved gas analysis in oil (DGA) is an important tool to identify the failure of transformers, and can discover the internal fault of the transformer in time. Gases analyzed by DGA mainly include H_2、CH_4、C_2H_4、C_2H_6、C_2H_2, so these five gases can be regarded as characteristic parameter of the standard failure models. 9 characteristic models are selected: normal without failure, low temperature overheat (＜300℃), middle temperature overheat (300~700℃), high temperature overheat (＞700℃), partial discharge, low energy discharge, high energy discharge, low energy discharge with overheat, and high energy discharge with overheat. The corresponding relations between standard failure models and gases are as follows:

Table 1. Failures and Corresponding Feature Values of Transformer

Failure model	H_2 Minimum	H_2 maximum	CH_4 Minimum	CH_4 maximum	C_2H_4 Minimum
normal	28.395	34.705	13.248	16.192	9.729
Low temperature overheat	9.45	11.55	22.68	27.72	16.533
middle temperature overheat	17.676	21.604	30.96	37.84	29.547

high temperature overheat	10.233	12.507	19.449	23.771	47.907
Partial discharge	78.57	96.03	5.814	7.106	0.963
Low energy discharge	48.753	59.587	19.503	23.837	4.437
High energy discharge	43.407	53.053	17.361	21.219	17.424
Low energy discharge with overheat	11.106	13.574	35.532	43.428	8.1
High energy discharge with overheat	11.178	13.662	28.665	35.035	24.093

Table 1 (Continue)

Failure model	H_2 Minimum	H_2 maximum	CH_4 Minimum	CH_4 maximum	C_2H_4 Minimum
normal	11.891	37.881	46.299	0.747	0.913
Low temperature overheat	20.207	41.337	50.523	0	0
middle temperature overheat	36.113	11.817	14.443	0	0
high temperature overheat	58.553	10.197	12.463	2.214	2.706
Partial discharge	1.177	4.653	5.687	0	0
Low energy discharge	5.423	1.053	1.287	16.254	19.866
High energy discharge	21.296	1.341	1.639	10.467	12.793
Low energy discharge with overheat	9.9	1.98	2.42	33.282	40.678
High energy discharge with overheat	29.447	6.696	8.184	19.368	23.672

The failure data of the transformer to be tested is shown in Table 2:

Table 2. Feature Value of Failures to be Tested

Feature value	H_2	CH_4	C_2H_4	C_2H_6	C_2H_2
Failures to be tested	1565.00	93.00	47.00	34.00	0.00

Standard failure model established by the replacement of failure characteristics with each indicator is as follows:

$$RX_1 = \begin{bmatrix} \mathrm{RI}_1 & c_1 & (28.395, 34.705) \\ & c_2 & (13.248, 16.192) \\ & c_3 & (9.729, 11.891) \\ & c_4 & (37.881, 46.299) \\ & c_5 & (0.747, 0.913) \end{bmatrix}; \quad RX_2 = \begin{bmatrix} \mathrm{RI}_2 & c_1 & (9.45, 11.55) \\ & c_2 & (22.68, 27.72) \\ & c_3 & (16.533, 20.207) \\ & c_4 & (41.337, 50.523) \\ & c_5 & (0, 0) \end{bmatrix};$$

$$RX_3 = \begin{bmatrix} \mathrm{RI}_3 & c_1 & (17.676, 21.604) \\ & c_2 & (30.96, 37.84) \\ & c_3 & (29.547, 36.113) \\ & c_4 & (11.817, 14.443) \\ & c_5 & (0, 0) \end{bmatrix}; \quad RX_4 = \begin{bmatrix} \mathrm{RI}_4 & c_1 & (10.233, 12.507) \\ & c_2 & (19.449, 23.771) \\ & c_3 & (47.907, 58.553) \\ & c_4 & (10.197, 12.463) \\ & c_5 & (2.214, 2.706) \end{bmatrix};$$

$$RX_5 = \begin{bmatrix} \mathrm{RI}_5 & c_1 & (78.57, 96.03) \\ & c_2 & (5.814, 7.106) \\ & c_3 & (0.963, 1.177) \\ & c_4 & (4.653, 5.687) \\ & c_5 & (0, 0) \end{bmatrix}; \quad RX_6 = \begin{bmatrix} \mathrm{RI}_6 & c_1 & (48.753, 59.587) \\ & c_2 & (19.503, 23.837) \\ & c_3 & (4.437, 5.423) \\ & c_4 & (1.053, 1.287) \\ & c_5 & (16.254, 19.866) \end{bmatrix};$$

$$RX_7 = \begin{bmatrix} \mathrm{RI}_7 & c_1 & (43.407, 53.053) \\ & c_2 & (17.361, 21.219) \\ & c_3 & (17.424, 21.296) \\ & c_4 & (1.341, 1.639) \\ & c_5 & (10.467, 12.793) \end{bmatrix}; \quad RX_8 = \begin{bmatrix} \mathrm{RI}_8 & c_1 & (11.106, 13.574) \\ & c_2 & (35.532, 43.428) \\ & c_3 & (8.1, 9.9) \\ & c_4 & (1.98, 2.42) \\ & c_5 & (33.282, 40.678) \end{bmatrix};$$

$$RX_9 = \begin{bmatrix} \mathrm{RI}_9 & c_1 & (11.178, 13.662) \\ & c_2 & (28.665, 35.035) \\ & c_3 & (24.093, 29.447) \\ & c_4 & (6.696, 8.184) \\ & c_5 & (19.368, 23.672) \end{bmatrix}.$$

Failure model to be tested:

$$RX_0 = \begin{bmatrix} \mathrm{RI}_0 & c_1 & 1565 \\ & c_2 & 93 \\ & c_3 & 47 \\ & c_4 & 34 \\ & c_5 & 0.00 \end{bmatrix}.$$

Based on the method of weight analysis of characteristics, the weight of each failure characteristic is obtained:

Table 3. Weighs of Features

Feature	H_2	CH_4	C_2H_4	C_2H_6	C_2H_2
Weight	0.170	0.179	0.215	0.160	0.275

Determine the distance between failure data to be tested and the standard failure model and standardize it. The standardized distance is as follows:

Table 4. Standard Deviation

Number	C_1	C_2	C_3	C_4	C_5
X_1	1.000	1.000	1.000	1.000	1.000
X_2	1.419	2.194	1.968	1.096	0.000
X_3	1.237	3.242	3.821	0.274	0.000
X_4	1.401	1.784	6.434	0.229	2.963
X_5	-0.109	0.059	0.217	0.075	0.000
X_6	0.550	1.792	0.247	0.019	21.759
X_7	0.668	1.521	2.095	0.009	14.012
X_8	1.382	3.821	0.768	0.000	44.554
X_9	1.380	2.951	3.044	0.132	25.928

Based on the weight and standard distance above, the correlation coefficient between failure to be tested and standard failure model can be obtained. Multiply correlation coefficient by corresponding weight, and the correlation degree can be obtained:

Table 5. Correlation Coefficient and Correlation Degree

Number	C_1	C_2	C_3	C_4	C_5	Correlation degree
X_1	0.952	0.952	0.952	0.952	0.952	0.947
X_2	0.936	0.906	0.914	0,948	0.995	0.944
X_3	0.943	0.869	0.849	0.982	0.955	0.931
X_4	0.936	0.921	0.772	0.985	0.878	0.891
X_5	1.000	0.992	0.985	0.991	0.955	0.992
X_6	0.971	0.921	0.984	0.995	0.503	0.840
X_7	0.966	0.931	0.909	0.995	0.610	0.885
X_8	0.937	0.849	0.962	0.995	0.331	0.770
X_9	0.937	0.879	0.875	0.989	0.459	0.791

Through the comparison of the correlation degree, we can find that the failure model to be tested has highest correlation with standard failure model X_5. Therefore, the failure of the equipment is X_5, namely partial discharge. This finding is in accordance with the real situation, showing the effectiveness and feasibility of this failure diagnosis method based on extension theory. When two or more figures are much higher than others, it can be inferred that more than one fault occur to the equipment. The traditional DGA can only detect one failure model. Thus, when more than one fault occur, the method based on extension theory is more effective.

4. Conclusion

This paper proposes an extension model and algorithms for the failure diagnosis of complex equipment based on extension theory. First, it establishes failure analysis models by analyzing different failure diagnosis information based on matter element model. Next, it provides the extensive distance of the failure information analysis, extensive correlation functions and algorithms for extensive correlation degree, based on which determines the failure type and conducts fast analysis of equipment failure. It is seen from the real case that the extension model of failure diagnosis for complex mechanical equipment based on extension theory can effectively support failure diagnosis and improve efficiency, providing a solution to the implementation of intelligent design of products.

References

[1] R. J. Patton and M. Hou, "Design of fault detectin and isolation observers: a matrix pencil approach", Automatica, vol. 34, no. 9, **(1998)**, pp. 1135-1140.
[2] M. Z. Chen, D. H. Zhou and G. R. Liu, "A new particle predictor for fault prediction of nonlinear time-varying systems", Developments in chemical Engineering and Mineral Processing, vol. 13, no. 3, **(2005)**, pp. 379-388.
[3] S. Jiye, X. Minqiang and W. Rixin, "Bayesian Model-based Fault Diagnosis for the Rotor", Aircraft Engineering and Aerospace Technology, vol. 81, no. 1, **(2009)**, pp. 19-24.
[4] D. Yuncheng, S. Hongrui and Y. Xiaobo, "A survey of fault diagnosis methods in control systems", Industrial Instrumentation & Automation, vol. 5, **(2008)**, pp. 9-13.
[5] J. H. Luo, K. R. Pattipati, L. Qiao and S. Chigusa, "An Integrated Diagnostic Development Process for Automotive Engine Control Systems", IEEE Transactions on Systems,Man,and Cybernetics-Part C:Applications and Reviews, vol. 37, no. 6, **(2007)**, pp. 1163-1173.
[6] M. Ge, Y. S. Xu and R. X. Du, "An Intelligent Online Monitoring and Diagnostic System for Manufacturing Automation", IEEE Transactions on Automation Science and Engineering, vol. 5, no. 1, **(2008)**, pp. 127-139.
[7] D. Wu, "Supplier selection in a fuzzy group setting: A method using grey related analysis and Dempster-Shafer theory", Expert Systems with Applications, vol. 36, no. 5, **(2009)**, pp. 8892-8899.
[8] R. Mohammad, T. Akbarzadeh and M. M. Khorasani, "A hierarchical fuzzy rule-based approach to aphasia diagnosis", Journal of Biomedical Informatics, vol. 40, no. 5, **(2007)**, pp. 465-475.
[9] V. Sugumaran and K. I. Ramachandran, "Automatic rule learning using decision tree for fuzzy classifier in fault diagnosis of roller bearing", Mechanical Systems and Signal Processing, vol. 21, no. 5, **(2007)**, pp. 2237-2247.
[10] P. E. Themis, G. T. Markos, P. E. Costas, *et al.*, "A methodology for the automated creation of fuzzy expert systems for ischaemic and arrhythmic beat classification based on a set of rules obtained by a decision tree", Artificial Intelligence in Medicine, vol. 40, no. 3, **(2007)**, pp. 187-200.
[11] C. Wen and Y. Chunyan, "Basics and Methods of Extenics", Science Bulletin, vol. 58, no. 13, **(2013)**, pp. 1190-1199.
[12] C. Wen, Y. Chunyan and H. Bin, "Basics Extension Logics", Beijing: Science Press, **(2003)**.
[13] Z. Yanwei, S. Nan, Z. Feng, *et al.*, "Configuration Design Method for Product Family Based on Extension Case Reasoning", Journal Of Mechanical Engineering, vol. 46, no. 15, **(2010)**, pp. 146-154.
[14] W. Tichun and H. Xiang, "Complex Mechanism Extension Scheme Design Model Based on Knowledge Reuse", Journal of Nanjing University of Aeronautics & Astronautics, vol. 44, no. 4, **(2012)**, pp. 548-552.
[15] G. Jingzhong, Q. Jing, L. Guoxi and L. Wei, "Extension approach for product module variant design", Computer Integrated Manufacturing Systems, vol. 14, no. 7, **(2008)**, pp. 1256-1267+1312.
[16] Z. Yanwei and Z. Guoxian, "Extension thought method of the trouble diagnosis and its application". Chinese journal of mechanical engineering, vol. 37, no. 9, **(2011)**, pp. 39.