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Study on Fault Prediction of Equipments Based on Extension Theory

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Abstract

Due to the lack of condition monitoring and health analysis of the equipment in the daily operations, serious accident happened and it caused the incorrect results of fault diagnosis. We propose a method of condition monitoring and fault prediction based on extension theory. The method established a matter element mode to give the formal description of the state of the equipment. It used dependent function to do the qualitative and quantitative analysis of the equipment state. Through the method, we can change the model of maintenance which is always done after fault occurred. We use the method on the example of turbines to prove the feasibility and effectiveness of the method.

Key words: *Extension theory, Fault prediction, Side distance, Matter element mode*

1. Introduction

Mechanical failure is one whose work does not meet the requirements in accordance with the provisions of the state. The common practice is a kind of afterwards maintenance mode that uses various diagnostic methods to diagnose the cause of the fault until the machine fails which greatly reduces the life of the machine [1]. Monitoring of the current machine status can not only provide the basis for the next stage of fault diagnosis, but also timely predict failures occurred. And it favored daily maintenance of the machine. The improvement of the early fault diagnosis technology can be early detected and prevented, and early to take effective measures is an important premise security to ensure safe and reliable operation of the system [5]. This year, there have been a number of scholars studied the fault prediction. Zeng Sheng-kui, Michael G. Pecht put forward a fault prediction of man - machine - complete cognitive loop model, give PHM technology image, analysis and quantitative evaluation on the predicting technical performance requirements. Xu Liang put forward failure prediction technology which support condition based repair. It arranges maintenance activities according to the development of current and future equipment forecast, meet the needs of different users [4]. These research systems conduct the prediction of failure, compare the afterwards maintenance mode in the past and timely maintain the system, reducing the difficulty of fault diagnosis and improving the life of the machine. However, the method lacks formal description of the system, and these methods have been established on the basis of full data. And due to the large amount of information of the system state you will not get good data, the incomplete of data lead to ambiguity and uncertainty of some of the factors. This paper

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introduces the extension theory to solve these problems, the establishment of a predictive model based on extension theory, proposed a comprehensive evaluation method of failure prediction based on extension theory. The method can determine system status effectively and accurately through a combination of qualitative and quantitative analysis methods and improve the accuracy and reliability of the forecasts, thus providing a new and effective way for failure prediction.

2. The Establishment of the Extension Model of Failure Prediction

The actual monitoring of the information contained in a large amount of data, and the focus of building on these models is to conduct appropriate formal description appropriately on the information which has been obtained [3]. Primitive theory of extenics provide new information describing formal tool for information description, which is available to study and resolve contradictions from both qualitative and quantitative point of view. In primitive theory, if the object is only one feature, take the ordered triple $R=(O,\ c,\ v)$ which is composed by objects *O*, characteristics *c*, and magnitude *v* which is *O* on the magnitude of *c* as n dimensional element. And if the object contains multiple features, take the array $R=(O,\ c,\ v)$ which is composed by object *O*, n features of the object $c_i\left(i=1,2\cdots,n\right)$, and magnitude $v_i\left(i=1,2\cdots,n\right)$ which is *O* on the magnitude of c_i as n dimensional element.

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

When things are changing with time, it can be described by the dynamic matter-element $R(t)=(O(t),c,v(t))$.

Where the matter-element *I*, affair element *Q* and relationship element *A* collectively called element *R*. Basic element theory use matter-element, affair element and relationship element to describe the object being studied. Matter element *I* is used to describe specific things and other static knowledge. When exists action, the characteristic action, or things are interacted with each other, it is described by affair element *Q*. And the interconnection constraint and other relational knowledge that exist between thing and thing, object and object, or thing and object, described by relationship element *A*. Hybrid knowledge use the composite element description. Thus, primitive and composite element is able to describe various data monitoring formalized. Using extension model to represent the monitoring data can not only express determinacy knowledge but also express uncertainty knowledge, make the computer express, storage and processing conveniently, to solve the contradiction between fault prediction.

As seen above, mode of expression of extension knowledge pay attention to entirety, emphasizing the characteristics of things, combined with magnitude to be considered as a whole, combined with its characteristics, matter-element model of fault diagnosis can be defined as follows:

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

Among it, S_i is m-state levels that is divided by machinery and equipment evaluation index, n is the number of features of the first i standard state model in the system I, $x_i(j)$ is the characteristic values of the first j feature of the system.

The measured data that monitored for forecasting is:

$$S_0 = \begin{bmatrix} I_0 & c_1 & x_0(1) \\ & c_2 & x_0(2) \\ & \vdots & \vdots \\ & c_n & x_0(n) \end{bmatrix} \quad (3)$$

Here the characteristic data $x_0(k)$ can be either a specific value or the interval.

3. Research on System Failure Prediction Method based on the Extension Theory

Extension theory provides an effective means to evaluate the current state of affairs. Its characteristic is using the correlation function of matter element to establish multi-index parameter matter element model, get classical domain and joint domain through the evaluation of the level and the measured data, then degree of association is gotten by using comprehensive evaluation method. It is a new approach to research on the problems of failure prediction from the two angles of qualitative and quantitative.

3.1 Determine Classical Domain and Joint Domain of Things

Model equipment operating status can be obtained from the statistical analysis of the historical database of statistical identification and detection. For a given device I, running state be divided into m grades from excellent to poor, and there are n malfunction indicators. Device status evaluation standard mode $X_i = \begin{bmatrix} I_i & c_1 & x_i(1) \\ & c_2 & x_i(2) \\ & \vdots & \vdots \\ & c_n & x_i(n) \end{bmatrix}$ $i = 1, 2, \cdots, k$, among it, $M_j = (c_j \quad x_i(j))$ is characteristic element, $X_i(j) = (a_{ij},\ b_{ij})$ is the system in state mode I_i corresponding characteristics of c_j index value of all possible changes, and said x_{ij} classical domain.

S is the whole state machine model, $X_i^{'}(j) = (a_{ij}^{'},\ b_{ij}^{'})$ is the state of all types of the magnitude of the total range of features c_j, Then X'_{ij} is the joint domain that the system characterized by c_j section

3.2 The Distance and Side Distance of Failure Prediction Information

Types of actual monitoring information can be divided into two types, that are set point value measured by instrument and the fuzzy interval that get because of loss of information. Therefore the fault prediction information processing can be divided into two major categories of point and interval.

1、 Point value type status information

When the measured value of the state information is a specific value, the distance between information and standard state interval is the one between point and interval. When the point is in the outside the interval, the distance between the point and interval is the one between the point and the nearest end point of the interval distance. When a point is in the interval, the distance is zero considered from classical mathematical. In order to describe the degree of the nature one thing has, extenics defined to represent the distance between the point and the interval. Set the point value x, the interval $X=(x_1,\ x_2)$, here define the distance of point value type failure prediction information:

$$l(x,X)=\left|x-\frac{x_1+x_2}{2}\right|-\frac{x_2-x_1}{2} \tag{4}$$

Among it, l is the extension distance that indicates state information. Here the interval can be either open interval or closed. If $x<x_1$ or $x>x_2$, then $l>0$. If $x\in(x_1,x_2)$, then $\rho\le 0$. And if $x=\frac{x_1+x_2}{2}$ then ρ is the smallest indicated that the point x from the interval X recently that is the optimum point at the midpoint of the interval (x_1,x_2). As for efficiency, the less time the better, but the requirement of the quality of product is as high as possible. And when the cost is calculated, it should be as low as possible.

Given the standard state model interval $X=(x_1,\ x_2)$, if the optimum point $x_0\in(x_1,\ \frac{x_1+x_2}{2})$ then

$$l=\begin{cases} x_1-x & x\le x_1\\ x-x_2 & x\ge x_0\\ (x_2-x_0)(x-x_1)/(x_1-x_0) & x\in(x_1,x_0)\end{cases} \tag{5}$$

Known as the left side distance that the state information x with regard to the point x_0 standard state interval X, written $l_L(x,x_0,X)$.

Given the standard state model interval $X=(x_1,\ x_2)$, if the optimum point $x_0\in(\frac{x_1+x_2}{2},\ x_2)$ then

$$l=\begin{cases} x_1-x & x\le x_0\\ x-x_2 & x\ge x_2\\ (x_1-x_0)(x_2-x)/(x_2-x_0) & x\in(x_0,x_2)\end{cases} \tag{6}$$

Known as the right side distance that the state information x with regard to the point x_0 standard state interval X, written $l_R(x,x_0,X)$.

2、 Interval status information

Due to the complexity of the systems and uncertainty of information, it is difficult to obtain accurate information and much uncertain information appears in information data in the form of interval [9]. In order to discuss the distance between interval and interval of the detected information, definite the interval distance. Let two failure prediction information interval $X_1=(x_1,\ x_2)$, $X_2=(x_3,\ x_4)$, then:

$$l(X_1,X_2)=\frac{1}{2}(l(x_1,X_2)+l(x_2,X_2)) \tag{7}$$

Called the distance between the state information interval X_1 and X_2 that is status Information interval distance.

For the concept of the midside distance of the interval type status information, given the interval $X_1=(x_1,\ x_2)$, $X_2=(x_3,\ x_4)$ and the optimum point $x_0\in(x_3,\ \frac{x_3+x_4}{2})$,then

$$l=\begin{cases} x_3-x_1, & \dfrac{x_1+x_2}{2}\le x_3 \\ (x_4-x_0)(x_1-x_3)/(x_1-x_0), & x_3\le\dfrac{x_1+x_2}{2}\le x_0 \\ x_2-x_4, & \dfrac{x_1+x_2}{2}\ge x_0 \end{cases} \qquad (8)$$

Known as the left side distance that interval X_1 with regard to the point x_0 and the interval X_2, written $l_L(X_1, x_0, X_2)$.

And given the interval $X_1=(x_1,\ x_2)$, $X_2=(x_3,\ x_4)$ and the optimum point $x_0\in(\frac{x_3+x_4}{2},\ x_4)$,then

$$l=\begin{cases} x_3-x_1, & \dfrac{x_1+x_2}{2}\le x_0 \\ (x_3-x_0)(x_4-x_2)/(x_4-x_0), & x_0\le\dfrac{x_1+x_2}{2}\le x_4 \\ x_2-x_4, & \dfrac{x_1+x_2}{2}\ge x_4 \end{cases} \qquad (9)$$

Known as the right side distance that interval X_1 with regard to the point x_0 and the interval X_2, written $l_R(X_1, x_0, X_2)$.

3.3 Determine the State Feature Weights

There are various features in one system, the more complex the system, the more features it has, various features are also divide into different degrees. The weight coefficient is used to measure the degree of importance of each feature, it can be written by $\alpha=\alpha_1,\ \alpha_2,\cdots,\ \alpha_n$, and $\sum_{j=1}^{n}\alpha_j=1$. When more than one layer which can be divided into several subsystems. It can be expressed as following:

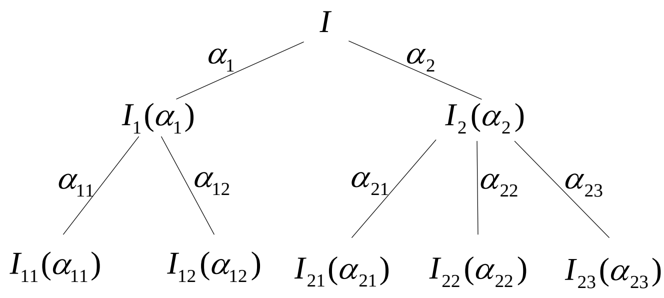

Figure 1. System Weight Analysis System Diagram

Among it, I is the total system -- the sum of the individual subsystems, I_1 and I_2 for the subsystem. I_{11} and I_{12} are constituent part of I_1. I_{22} and I_{23} are constituent part of I_2. The final analysis of the system tree is each feature vector, wherein α_1 , α_1 , α_1 as the weighting coefficients, and satisfy the following relation:

$$\begin{cases} \alpha_1 + \alpha_2 = 1 \\ \alpha_{11} + \alpha_{12} = 1 \\ \alpha_{21} + \alpha_{22} + \alpha_{23} = 1 \end{cases} \qquad (11)$$

There are too much data monitored in the process of failure prediction, and the confirm of the weight of each feature is the the key to properly assess the state of the system. The accuracy of determination of weight directly impact on the final prediction accuracy of the results. Currently there are many ways to determine the weight, such as arithmetic method, analytical hierar-chy process, regression analysis method, *etc.*, [12]. Wherein the analytical hierar-chy process is applied in more times, but when constructing judgment matrix, it also has strong subjectivity. Considering that grey relational analysis in the grey system is the analysis of the size of correlation degree between things and factors in the grey system. The size of grey correlative degree directly reflects the degree of influence between two things. In this paper, gray correlation analysis is used to determine the weight of feature, and this result is more objective.

If there are two sequences $X_1 = (x_1(1), x_1(2), \cdots, x_1(n))$ and $X_i = (x_i(1), x_i(2), \cdots, x_i(n))$, then the correlation coefficient of X_1 and X_2 is:

$$\gamma_i(k) = \frac{\min\limits_i \min\limits_k |x_1(k) - X_i(k)| + \beta \max\limits_i \max\limits_k |x_1(k) - X_i(k)|}{|x_1(k) - X_i(k)| + \beta \max\limits_i \max\limits_k |x_1(k) - X_i(k)|} \quad \beta \in (0,1), \quad k = 1,2,\cdots n \qquad (12)$$

Because the standard state pattern data of the fault prediction is not an accurate value, but is described by interval, so the above formula is not applicable. At this time correlation coefficient formula is needed to use for interval data:

Suppose that the standard state pattern matrix is:

$$\mathbf{A} = \begin{bmatrix} (\overset{-}{a}_{11}, \overset{+}{a}_{11}), (\overset{-}{a}_{12}, \overset{+}{a}_{12}), \cdots, (\overset{-}{a}_{1n}, \overset{+}{a}_{1n}) \\ (\overset{-}{a}_{21}, \overset{+}{a}_{21}), (\overset{-}{a}_{22}, \overset{+}{a}_{22}), \cdots, (\overset{-}{a}_{2n}, \overset{+}{a}_{2n}) \\ \cdots\cdots\cdots \\ (\overset{-}{a}_{m1}, \overset{+}{a}_{m1}), (\overset{-}{a}_{m2}, \overset{+}{a}_{m2}), \cdots, (\overset{-}{a}_{mn}, \overset{+}{a}_{mn}) \end{bmatrix},$$

make $(\overset{-}{b}_{ij}, \overset{+}{b}_{ij}) = (-\overset{+}{a}_{ij}, -\overset{-}{a}_{ij})$,and $\overset{+}{u}_j = \max \overset{+}{b}_{ij}$, $\overset{-}{u}_j = \max \overset{-}{b}_{ij}$, then the grey correlation coefficient is

$$\gamma_i(k) = \frac{\min\limits_i |\Delta_{ij}| + \beta \max\limits_i |\Delta_{ij}|}{|\Delta_{ij}| + \beta \max\limits_i |\Delta_{ij}|} \quad \beta \in (0,1), \quad k = 1,2,\cdots n \qquad (13)$$

Among it, $|\Delta_{ij}| = \left| (\overset{-}{u}_j, \overset{+}{u}_j) - (\overset{-}{b}_{ij}, \overset{+}{b}_{ij}) \right| = \max(\overset{-}{u}_j - \overset{-}{b}_{ij}, \overset{+}{u}_j - \overset{+}{b}_{ij})$.

And resolution ratio $\beta \in (0,1)$ .Its value objectively reflect the degree that researcher pay attention to $\max\limits_i \max\limits_k |x_1(k) - X_i(k)|$ and indirect impact of various factors on the system's correlation degree. Here take $\beta = 0.5$ [10]. Then the correlation degree of X_1 and X_2 is:

$$\gamma_i = \frac{1}{n} \sum_{k=1}^{n} \gamma_{1i}(k) \qquad (14)$$

The weight of each feature can be obtained by dealing with normalization processing:

$$\alpha_i = \frac{\gamma_i}{\sum_{k=1}^{n} \gamma_i} \tag{15}$$

3.4 Correlation Function

Fault prediction correlation function can be defined as follows:

$$k_{ij} = \begin{cases} \dfrac{l(x_0(j),\ X_i(j))}{l(x_0(j),\ X_i'(j)) - l(x_0(j),\ X_i(j))} & l(x_0(j),\ X_i'(j)) - l(x_0(j),\ X_i(j)) \neq 0 \\ -l(x_0(j),\ X_i(j)) - 1 & l(x_0(j),\ X_i'(j)) - l(x_0(j),\ X_i(j)) = 0 \end{cases} \tag{16}$$

Among it, k_{ij} indicates extension association degree that the device status j to be predictive regarding to the device state grade i. Here the distance l can represent either the general distance or the side distance.

3.5 Method of Equipment Fault Prediction

The basic train of thought based on extension theory is that taking the standard state sample element obtained as a reference indicator element, establishing fault prediction matter element according to monitoring data, calculating correlation degree of the evaluation matter element and target matter element through the correlation function, then evaluating the current state of equipment. Figure 2 shows the basic principle of fault prediction.

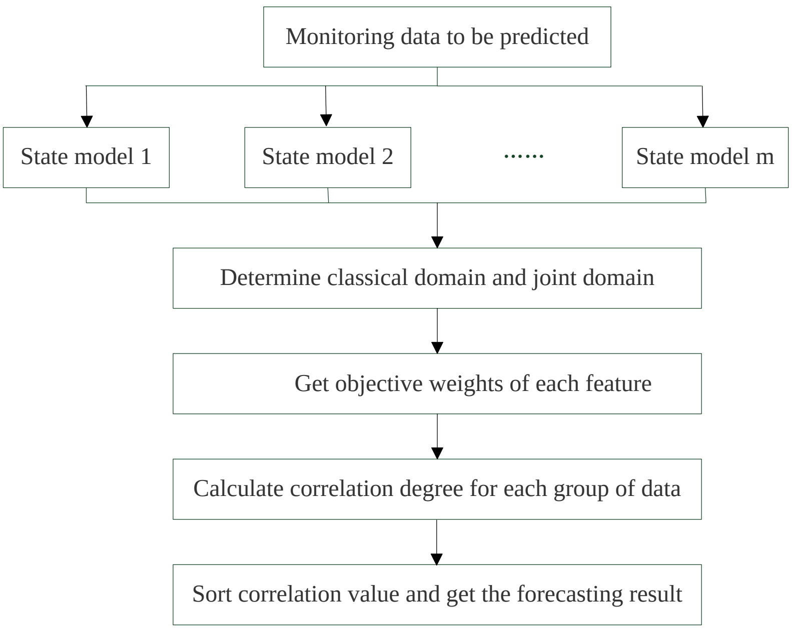

Figure 2. Flow Chart of Fault Prediction Method

The concrete steps of prediction are as following:

Step 1, determine the standard of measurement.

Step 2, determine classical domain X_{ij} and joint domain X_{ij}'.

Step 3, determine the weight coefficient of each feature.

Step 4, the first evaluation: remove the conditions that must be met.

Step 5, gain the distance and side distance of evaluation of information and standard index referenced by using the concept of distance and side distance in chapter 3.2.

Step 6, calculate the correlation coefficient k_{ij} of the system by using correlation function（16）.

Step 7, obtain the comprehensive correlative degree $K_s(I)=\sum_{i=1}^{n}\alpha_j k_{ij}$ that the evaluation system I about the level of S.

Step 8, determine what state the system is. If $K(I)=\max K_s(I)$ then the system is in this state at this moment.

4. Application Example

Fault diagnosis of steam turbine in the literature [11], for example, to verify the above method. The turbine consists of two subsystems, the rotor bearing system and the circulation part (See Figure 2). According to the actual situation and the past running history of the machine, the device operation is divided into four grades standard: good, normal, poor, warning (see Table 1).

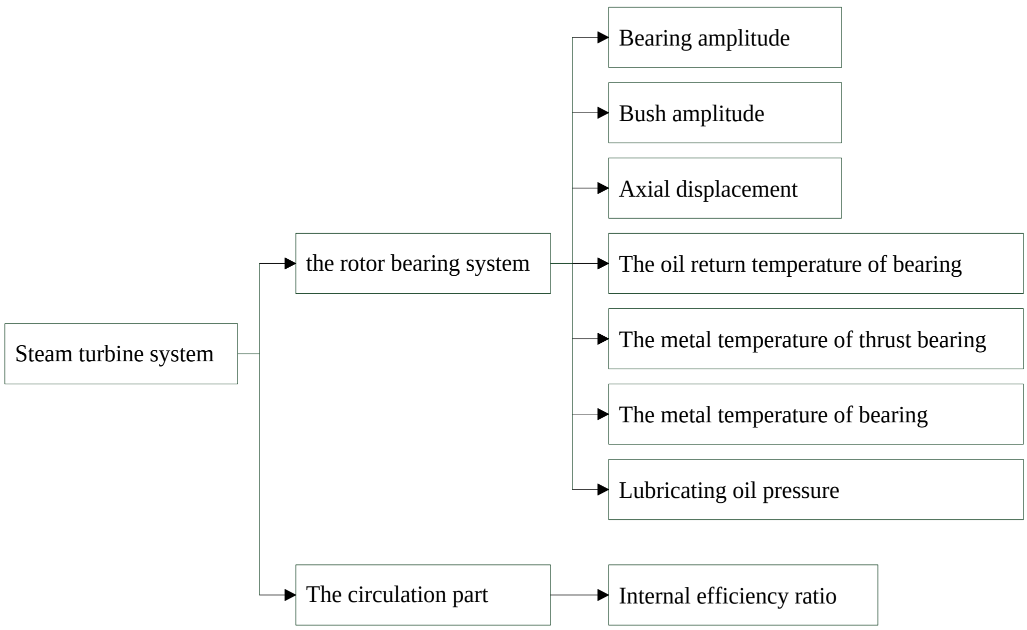

Figure 2. Steam Turbine System

Table 1. Evaluation Grade Criterion

Evaluation grade	Good	Normal	Poor	Warning
Bearing amplitude /μm	(0, 25)	(25, 60)	(60, 90)	(90, 120)
Bush amplitude /μm	(0, 15)	(15, 30)	(30, 45)	(45, 70)
Axial displacement /mm	(0, 0.6)	(0.6, 0.9)	(0.9, 1.2)	(1.2, 1.4)
The oil return temperature of bearing / ℃	(59, 60.5)	(60.5, 61.5)	(61.5, 63)	(63, 65)
The metal temperature of thrust bearing / ℃	(79, 81)	(81, 84)	(84, 87)	(87, 90)
The metal temperature of bearing / ℃	(60, 65)	(65, 68)	(68, 71)	(71, 75)

Lubricating oil pressure /*MPa*	(0.07, 0.09)	(0.09, 0.12)	(0.12, 0.13)	(0.14, 0.15)
Internal efficiency ratio / ε	(0.9, 1.0)	(0.8, 0.9)	(0.7, 0.8)	(0.5, 0.7)

The detected operating data can be expressed by n-dimensional matter-element as following:

$$X_0 = \begin{bmatrix} S_0 & c_1 & x_0(1) \\ & c_2 & x_0(2) \\ & \vdots & \vdots \\ & c_n & x_0(n) \end{bmatrix} = \begin{bmatrix} S_0 & c_1 & 30 \\ & c_2 & 16 \\ & c_3 & (0.7,1.0) \\ & c_4 & 62 \\ & c_5 & 85 \\ & c_6 & 69 \\ & c_7 & 0.11 \\ & c_8 & 0.81 \end{bmatrix}.$$

1、 Determine the classical domain and joint domain

The 8 characters from the bearing amplitude to internal efficiency ratio are represented by $c_1 \sim c_8$ in turn. Classical domains of the state level are as following:

$$S_1 = \begin{bmatrix} Good & c_1 & (0, 25) \\ & c_2 & (0, 15) \\ & c_3 & (0, 0.6) \\ & c_4 & (59, 60.5) \\ & c_5 & (79, 81) \\ & c_6 & (60, 65) \\ & c_7 & (0.07, 0.09) \\ & c_8 & (0.9, 1.0) \end{bmatrix}; \quad S_2 = \begin{bmatrix} Normal & c_1 & (25, 60) \\ & c_2 & (15, 30) \\ & c_3 & (0.6, 0.9) \\ & c_4 & (60.5, 61.5) \\ & c_5 & (81, 84) \\ & c_6 & (65, 68) \\ & c_7 & (0.09, 0.12) \\ & c_8 & (0.8, 0.9) \end{bmatrix};$$

$$S_3 = \begin{bmatrix} Poor & c_1 & (60, 90) \\ & c_2 & (30, 45) \\ & c_3 & (0.9, 1.2) \\ & c_4 & (61.5, 63) \\ & c_5 & (84, 87) \\ & c_6 & (68, 71) \\ & c_7 & (0.12, 0.13) \\ & c_8 & (0.7, 0.8) \end{bmatrix}; S_4 = \begin{bmatrix} Warning & c_1 & (90, 120) \\ & c_2 & (45, 70) \\ & c_3 & (1.2, 1.4) \\ & c_4 & (63, 65) \\ & c_5 & (87, 90) \\ & c_6 & (71, 75) \\ & c_7 & (0.14, 0.15) \\ & c_8 & (0.5, 0.7) \end{bmatrix}.$$

Determine the joint domain of state level :

$$S = \begin{bmatrix} I & c_1 & (0, 125) \\ & c_2 & (0, 75) \\ & c_3 & (0, 1.5) \\ & c_4 & (55, 70) \\ & c_5 & (75, 95) \\ & c_6 & (55, 80) \\ & c_7 & (0.05, 0.20) \\ & c_8 & (0.4, 1.0) \end{bmatrix}.$$

2、 Expressing the detected operating data by n-dimensional matter-element as following:

$$X_0 = \begin{bmatrix} S_0 & c_1 & x_0(1) \\ & c_2 & x_0(2) \\ & \vdots & \vdots \\ & c_n & x_0(n) \end{bmatrix} = \begin{bmatrix} S_0 & c_1 & 30 \\ & c_2 & 16 \\ & c_3 & 0.8 \\ & c_4 & 62 \\ & c_5 & 85 \\ & c_6 & 69 \\ & c_7 & 0.11 \\ & c_8 & 0.81 \end{bmatrix};$$

3、 Determine the weight

The weight set is determined by the gray correlation analysis method.

$$\begin{cases} \{\alpha_1, \ \alpha_2\} = \{0.55, 0.45\} \\ \{\alpha_{11}, \ \alpha_{12}, \ \alpha_{13}, \ \alpha_{14}, \ \alpha_{15}, \ \alpha_{16}, \ \alpha_{17}\} = \{0.281, 0.223, 0.124, 0.080, 0.161, 0.088, 0.043,\} \end{cases}$$

Finally the weight of each feature is determined:

$\alpha'_{11} = \alpha_1 \cdot \alpha_{11} = 0.155$; $\alpha'_{12} = \alpha_1 \cdot \alpha_{12} = 0.123$; $\alpha'_{13} = \alpha_1 \cdot \alpha_{13} = 0.068$; $\alpha'_{14} = \alpha_1 \cdot \alpha_{14} = 0.044$; $\alpha'_{15} = \alpha_1 \cdot \alpha_{15} = 0.088$; $\alpha'_{16} = \alpha_1 \cdot \alpha_{16} = 0.048$; $\alpha'_{17} = \alpha_1 \cdot \alpha_{17} = 0.024$; $\alpha'_{21} = \alpha_{21} = \alpha_2 = 0.45$;

4、 Calculate the correlation function and the correlation degree.

Table 2. Correlation Coefficient of Steam Turbine

Correlation coefficient	S_1	S_2	S_3	S_4
k_{1j}	－0.14	0.29	－0.5	－0.67
K_{2j}	－0.06	0.13	－0.47	－0.64
K_{3j}	－0.47	－0.08	－0.08	－0.35
K_{4j}	－0.18	－0.07	0.67	－0.13
K_{5j}	－0.29	－0.09	0.67	－0.17
K_{6j}	－0.27	－0.08	0.67	－0.15
K_{7j}	－0.25	0.67	－0.14	－0.33
K_{8j}	－0.32	0.20	－0.05	－0.37

The correlation degree correlation coefficient is obtained by combining the correlation coefficient and the weight: K_{s1}=－0.257 K_{s2}=0.147 K_{s3}=－0.04 K_{s4}=－0.409.

So, the correlation degree can be calculated: K_{smax}= K_{s2}=0.147. It is visible that the condition of equipment should be normal. And it is consistent with the actual results in literature [11].

5. Conclusion

This paper evaluates the state monitored by machinery based on the principle of extenics and provide guarantee for machine running of the next stage, considering comprehensively a variety of information of the mechanical operation and evaluating the state of the machinery qualitative and quantitative. Through the establishment of matter-element model that can describe the state of the mechanical system formally and standardly, machine running status can be analyzed accurately, the machine health status can be grasped, timely repaired and maintained, reducing the damage brought by maintenance of machine afterward, and improving the accuracy of machine fault diagnosis.

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