Design of a Simulation Platform for Fault Analysis of Hydraulic Rotating Machines using AHP

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***Abstract* — In this paper we study hydraulic rotating mechanism (HRM), and propose a new fault analysis approach for HRM using Analytic Hierarchy Process (AHP) method and Binary Tree Support Vector Machine (BT-SVM). In the algorithm, various impact factors of classification precision are comprehensively considered in 2 steps: i) weights of each type of fault are calculated using AHP, ii) and based on the weight results, classification sequences of all fault types are determined. Also, simulation experiments are conducted on the fault diagnosis of HRM using different methods. The results show that the algorithm is superior in both diagnosis efficiency and classification precision, and is also feasible and effective in fault diagnosis of HRM, thus providing a new method for the fault diagnosis of HRM.**

Keywords - T-S fuzzy; AHP; SVM; HRM; fault analysis

I. INTRODUCTION

In modernization production and construction, hoisting machinery has been playing an indispensable role, needless to say its importance to us. Within hoisting machinery, tower crane is a significant hoisting and transporting machinery in architecture construction while rotating mechanism is an extremely-important constitute of it. Frequent faults of rotating mechanism have severely affected the normal operation of the entire tower crane. It is very necessary to conduct fault tree analysis on the rotating mechanism of tower crane to ensure its safe and stable operation.

The AHP- and BT-SVM-based algorithm, which also combines with Boolean algebra and probability theory, has been widely adopted in evaluating and calculating the stability of complex system. The algorithm is a simple but effective analysis tool of system fault and is capable of conducting quantitative analysis on fault causes, which represents fault relation using "AND gate" and "OR gate" in logic diagram and estimates the probability of fault. Traditional SVW method has the following disadvantages: ①relation between events can only be expressed by "AND" and "OR", which is inadvisable to describe fault relation in real engineering practice as relation between faults are usually complicated, uncertain and fuzzy; ② traditional SVM analysis method is based on a large amount of fault data and precisely-known fault probabilities, which requires a large searching work. The above two points have limited the application of traditional fault tree and fault tree analysis in the analysis and diagnosis of system reliability.

The rotating mechanism system of tower crane is of complicated structure, tight logical relationship and certain hierarchy. Hence, the Thesis proposes a fuzzy AHP- and BT-SVM-based HRM fault analysis method which provides a multi-classification algorithm combining AHP and BT-SVM. First, the evaluation system is modeled using AHP and the weights of various faults are determined by comprehensively measuring several impact factors; then, all faults are ranked based on their weights, through which the structure of BT-SVM is also determined; finally, fault diagnosis analysis is conducted using the algorithm.

II. RELIABILITY ANALYSIS MODEL OF CRANE ROTATING MECHANISM

At present, the structure shown in Fig. 1 is generally adopted on domestic rotating mechanism of tower crane which is driven by motor and decelerated by planet gears. Besides, the mechanism is of small dimension, large transmission ratio and light weight. Now, let's analyze its reliability.

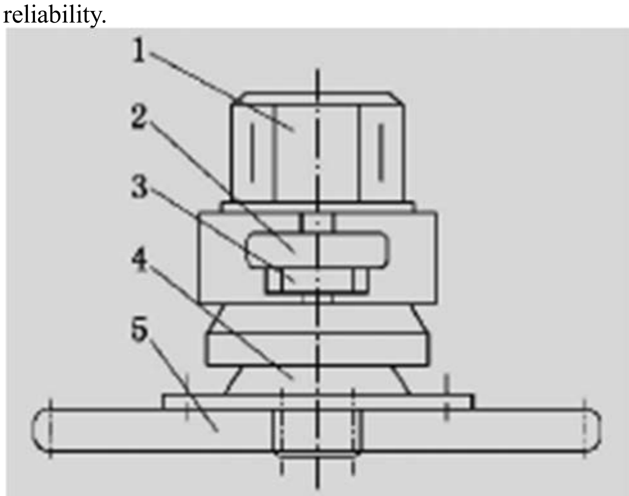

Figure 1. Schematic diagram of HRM

(1-Motor; 2-Hydraulic coupler; 3-Brake; 4-Planet gear decelerator; 5-Gear pair)

Based on the formation of the rotating mechanism in domestic tower crane, we divide rotating mechanism into power part, brake part and output part. Besides, based on the provided data and literature resulting from tracking the quality of many domestic tower crane, as well as the characteristics that the fault probability of the decelerator is high, we further divide the internal part of decelerator into 3 parts, box, shaft and gear, and list them into the fault tree. The established HRM fault tree is as shown in Fig. 2. Corresponding code for each component is: T --rotating mechanism, M_1 --decelerator, M_2 --output part, M_3 --power part, X_1 --brake, X_2 --motor, X_3 --hydraulic coupler, X_4 --gear pair, X_5 --decelerator shell, X_6 -- decelerator shaft and X_7 -- decelerator gear respectively.

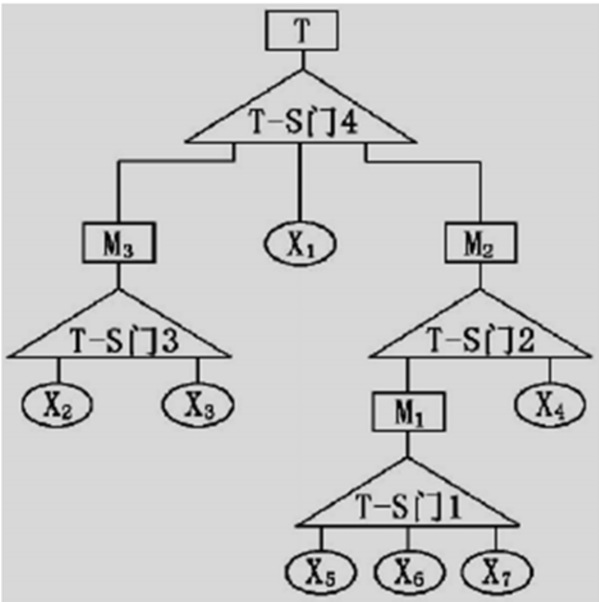

Figure 2. HRM T-S fuzzy tree
(Note: The "门" in the figure means "gate".)

III. AHP- AND BT-SVM-BASED ALGORITHM

The preceding part of the Thesis has mentioned that the structure of binary tree can largely affect the classification precision of BT-SVM. The improvement in the Thesis lies in that the binary tree structure is designed based on AHP. The AHP-based evaluating system is capable of designing significant value-degree-affecting indexes combining fault reality and experience from experts, measuring the value degrees of all faults by integrating several indexes, and obtaining a weight value from each kind of fault. Those weights determine the sequence of fault recognition; through the latter the binary tree structure is constructed.

AHP is a multi-objective and multi-criteria decision-making analysis method which decomposes a target to be evaluated into a multi-criteria one and determines the relative importance of each factor by introducing a proportion scale ranging from 1 to 9[6]. Meanwhile, it resolves complicated problems into several layers and factors and conducts simple comparison and calculation among all factors, resulting in weights of different schemes, which provides basis for selecting the best one[7].

Step 1: Build a hierarchical structure

Generally, the model consists of three layers, goal, criteria and alternatives, and relation between layers are represented in line. For the fault-diagnosis-based evaluating system, the goal is the value degree of faults; criteria are the impact factors which measuring those faults; and alternatives are fault status. HRM fault is a common motor fault resulting from causes like poor lubrication and incorrect assembly etc. It may also fail to function normally due to fatigue wear[8]. Therefore, it is of significant meaning to study the fault diagnosis of HRM.

Based on the reality of motor HRM, the measuring indexes for the criteria layer are set as: B_1 --sample distribution scope in high-dimension characteristic space of various faults, B_2 --fault frequency, B_3 --redemptive losses by diagnosis and B_4 --distribution spaces of sample types in high-dimension characteristic space of various faults. As a result, the weight in the evaluating system turns to be an integrated reflection of fault recognition rate, actual probability and theory division difficult degree. By selecting 4 status, normal, inner ring fault, outer ring fault and ball fault, as classification objectives, we establish a hierarchical structure as shown in Fig. 3.

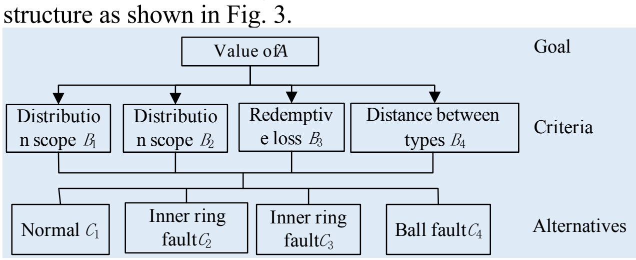

Figure 3. HRM-fault-diagnosis-based hierarchical structure

Step 2: Construct a comparison matrix

To quantify the qualitative analysis result, compare the importance of either two factors on the same layer with respect to the above layer, thus constructing a decision matrix.

$$\mathrm{A} = (a_{ij})_{n\times n} \tag{1}$$

Where a_{ij} is the ratio of the importance of factor a_i and a_j with respect to the criteria layer. The judgment matrix **A** has the following properties:

$$\begin{cases} a_{ij} > 0 \\ a_{ij} = 1/a_{ji} \\ a_{ii} = 1 \end{cases} \tag{2}$$

The importance of factors on the same layer is generally valuated based on a proportion scale ranging from 1 to 9, the meanings of which are listed in Table 1.

TABLE 1. PROPORTION SCALES AND THEIR MEANINGS OF THE JUDGMENT MATRIX

Scale	Meaning
1	Compared with each other, the two factors are of the same importance.
3	Compared with each other, the former is slightly important than the latter.
5	Compared with each other, the former is distinctly important than the latter.
7	Compared with each other, the former is greatly important than the latter.
9	Compared with each other, the former is extremely important than the latter.
2, 4, 6, 8	Intermediate values between the above adjacent judgments.

For HRM fault discussed in the Thesis, the judgment matrix between criteria B and goal A is constructed based on diagnosis experience as:

$$A = \begin{bmatrix} 1 & 3 & 3 & 5 \\ 1/3 & 1 & 1 & 3 \\ 1/3 & 1 & 1 & 3 \\ 1/5 & 1/3 & 1/3 & 1 \end{bmatrix} \tag{3}$$

Step 3: calculate weight using the judgment matrix

There are many methods to solve weight using judgment matrix, including adding method, minimum angle-off set and feature vector etc. in the Thesis, the third method is adopted. First, calculate the maximum feature value $\lambda_{\max}$ of matrix **A**; then obtain the corresponding positive feature vector (a feature vector of which all the components are larger than 0) based on Equation (4).

$$AW = \lambda_{\max} W \tag{4}$$

Where, $\lambda_{\max}$ is the maximum feature value of matrix **A**, W is the feature vector. By normalization processing, the weight vector is resulted.

The maximum feature value of judgment matrix **A** is calculated to be $\lambda_{\max} = 4.043$, thus the weight vector is

$W = (0.520, 0.201, 0.201, 0.078)$。

Step 4: Consistency check of matrix. The steps of consistency check are as follows:

① Calculate the consistency index of the judgment matrix

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

② Look up the average random consistency index RI from Table 2 based on the order of matrix.

TABLE 2. AVERAGE RANDOM CONSISTENCY INDEX

Order	1	2	3	4	5	6	7	8	9
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45

③ Calculate the consistency ratio CR

$$CR = \frac{CI}{RI} \tag{6}$$

If $CR < 0.1$, **A**'s consistency is satisfying and should be accepted; otherwise, give up **A** or conduct appropriate adjustment on **A**'s data. The check result is CR=0.016 < 0.1, representing the consistency is acceptable.

Step 5: Calculate the relative weight of alternatives with regard to overall goal

The above calculation result is only the weight vectors of each factor in criteria layer B with regard to goal A while our final objective is to obtain the weight vector of each factor in alternative layer C with regard to goal A. Therefore, we need to calculate the weight vectors of factors in alternative layer C with respect to criteria layer B, then synthesize the obtained weight vector and finally obtain the overall weight vector.

Thus, we establish the overall AHP- and BT-SVM-based model. Apply the model in fault diagnosis of HRM, the structure diagram is shown as follows.

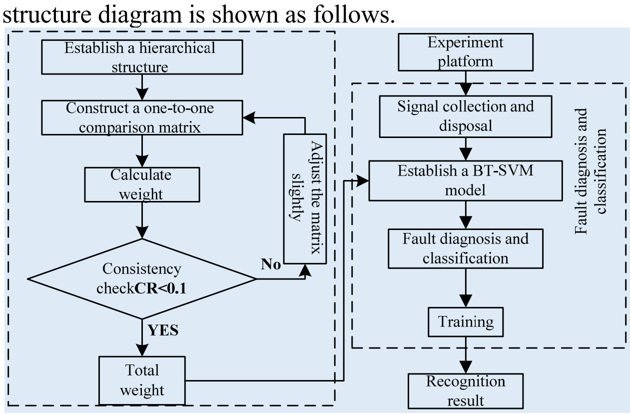

Figure 4. Structure chart of HRM fault diagnosis

IV. EXPERIMENT RESULT AND ANALYSIS

To verify the effectiveness of diagnosing motor HRM fault using the improved algorithm, we conduct simulation experiment using the HRM fault data provided by USA Case Western Reserve University and analyze the data by comparing with the algorithm. 50 groups of sample data (200 groups in total) are collected for each of the 4 fault status (normal, inner ring fault, outer ring fault and ball fault), in which 120 groups are used in training while the other 80 groups are used for testing.

It is obtained by calculation that the synthesized weight of each alternative with respect to the goal in the AHP- and BT-SVM-based HRM fault diagnosis model is (0.151, 0.238, 0.210, 0.401) and $CR = 0.024 < 0.1$, which proves that the synthesized weight is of good consistency. Therefore, the diagnosis sequence of HRM fault is: ball fault, inner ring fault, outer ring fault and normal.

To improve the calculation precision, genetic algorithm is adopted on the two important parameters which affect the performance of SVM, nuclear parameter and penalty parameter, to determine their values by virtue of optimization, which is of great effect[12]. Select the nuclear parameter in radial direction of SVM as

$$K(x, y) = \exp(-\frac{\|x-y\|^2}{2\delta}) \tag{7}$$

After optimizing SVM parameter using genetic algorithm, make parameter δ 4 and penalty parameter C 224.

First, input the feature vectors of the 120 groups of training samples into BT-SVM for training, then select 20 groups from the training samples for further training and calculate the training accuracy rate. Select another 80 group testing samples for testing, check their generalization and fault-tolerant capabilities, and calculate the accuracy rate of the testing. Express the algorithm in the Thesis using M1 and compare M1 with *M*2, *M*3, *M*4, *M*5 and *M*6 (the binary tree structure of *M*2 algorithm is designed based on fault frequency; binary tree structure of *M*3 algorithm is designed based on sample distribution scope; *M*4 represents one-to-more method; *M*5 represents one-to-one method; and *M*6 represents decision-making-oriented non-ring diagram method) to check the effect of the algorithm. The comparison results are as shown in Table 3.

TABLE 3. FAULT DIAGNOSIS RESULTS OF SEVERAL MULTI-CLASSIFICATION ALGORITHMS

Algorithm	SVM number	Diagnosis time/s	Accuracy rate of training/%	Accuracy rate of testing/%
*M*1	3	3	100	95.9
*M*2	3	6	99.2	94.5
*M*3	3	8	98.5	94.8
*M*4	4	14	97.6	93.6
*M*5	6	7	100	96.8
*M*6	6	4	97.6	91.2

It can be seen from the above comparison table that the diagnosis accuracy rates of AHP-based BT-SVM and one-to-one method are higher than the other algorithms; besides, the diagnosis time spent by the improved algorithm is shorter and the required SVM quantity is less. Therefore, the improved algorithm in the Thesis is of high diagnosis efficiency, good classification precision and preferable fault recognition ability.

V. CONCLUSIONS

The Thesis proposes a new fault analysis approach for motor HRM on the basis of AHP and BT-SVM which comprehensively takes into account various impact factors of classification precision, calculates weights of each kind of fault using AHP and determines classification sequences of all fault types based on the weight results. Besides, simulation experiments are conducted on the fault diagnosis of HRM using different methods. The results show that the algorithm is superior in both diagnosis efficiency and classification precision, and is also feasible and effective in fault diagnosis of HRM, thus providing a new idea for the fault diagnosis of HRM.

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