A STUDY ON DECISION TREE FOR INDUCTION MOTOR DIAGNOSTIC SYSTEM

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ABSTRACT

A Decision Tree based on the vibration analysis for induction motor is proposed to diagnose the motor status. Decision Tree is an expert system that builds the knowledge-based system from experiences and itself can play the role of a diagnosis tool. Vibration signals are collected from induction motor and processed to become inputs of the tree. From these input data, the tree will perform tests to give the final diagnostic result that shows the motor status. The paper also reviews the main problems of induction motor, and describes the abnormal frequency components in the machine fault induced vibration spectrum.

Keywords: Decision Tree, expert system, induction motor, diagnosis, vibration signal.

1. INTRODUCTION

In the last decade, induction motors are widely used in industry to perform different tasks. Therefore, any motor failure can cause expensive damage and production down time. The effectivity and productivity of the motors have become an important study field. Many studies have been developed to monitor the motor health. Most of them focus on two main methods, the first one is based on motor stator currents, and the second is based on vibration signals.

Vibration – based analysis for induction motor is a very popular and effective technique that has been used to diagnose the status of motor. This method monitors vibration signals to detect abnormal components in frequency domain which result from motor faults, watch the changes in motor vibration condition and analysis of the reasons of these changes. The paper will discuss on this method, and suggest decision tree as a motor condition monitoring program.

Decision tree is an expert system that able to process input data and act upon this data. It consists of a knowledge base, embodying the knowledge and experience of traditional human experts in the field. This paper will describe the construction of decision tree, and build the tree from the past experiences on vibration of induction motor which aim to the motor online fault diagnosis.

2.DECISION TREE

The decision tree is a diagnostic tool that builds the knowledge-based system by the inductive inference from case histories. The construction of the decision tree bases on a learning set containing a collection of measurements. A decision tree contains :

- leaf nodes (or answer nodes) which contain class name.
- decision nodes (or non-leaf nodes) that specifies some test to be carried out on a single attribute value, with one branch and sub-tree for each possible outcome of the test.

Structure of decision tree highly depends on how a test is selected as root of the tree. The criterion for selecting the root of the tree is Quilan's information theory (information gain). This criterion means the information that conveyed by a message depends on its probability and can be measured in bits as minus the logarithm to base 2 of that probability. The construction of decision tree bases on a training set T, which is a set of cases.

Each case specifies values for a collection of attributes and for a class. Let the classes be denoted $\{C_1, C_2, \ldots, C_k\}$. Suppose we have a possible test with n outcomes that partitions the training set T into subsets $T_1, T_2, \ldots, T_n$. Let S is any set of cases, $freq(C_i, S)$ is the number of cases in S that belong to class C_i , |S| is the number of cases in set S. If we select one case at random from set S and announce that it belongs to class C_j. This message has probability

$$\frac{freq(C_j, S)}{|S|}$$

and so the information it conveys is

$$-\log_2 \frac{freq(C_j, S)}{|S|} \text{ bits}$$

The expected information needed to identify the class of case in S :

$$\text{info(S)} = -\sum_{j=1}^{k} \frac{freq(C_j, S)}{|S|} \times \log_2 \left(\frac{freq(C_j, S)}{|S|} \right) \text{ bits}$$

When applied to the set of training cases, info(T) measures the average amount of information needed to identify the class of a case in T.

A similar measurement after T has been partitioned in accordance with n outcomes of a test X :

$$\text{info}_X(\text{T}) = \sum_{i=1}^{n} \frac{|T_i|}{|T|} \times \text{info}(\text{T}_i) \text{ bits}$$

The quantity

$$\text{Gain(X)} = \text{info(T)} - \text{info}_X\text{(T)}$$

measures the information that is gained by partitioning T in accordance with the test X. The gain criterion selects a test to maximize this information gain.

A lot of methods are developed based on this criterion such as ID3, C4.5, …. When decision tree was built, it can be used to classify a case by starting at the root of the tree and trace out the path until a leaf is encountered. This paper proposes a decision tree established upon vibration-based method, where vibration data is collected from accelerator sensors and processed to become input of decision tree. The tree will give a final decision of motor condition from this data.

3. INDUCTION MOTOR FAULTS AND DEFECTS

Machine failures are divided into electrical faults and mechanical faults. Each machine defect produces a unique set of vibration components that can be used for identification. This part will describe these vibration features for the most common machinery defects. These basic information needed to analyze unusual situations.

3.1 Mechanical Unbalance

An unbalance defect occurs when the center of mass of motor does not coincide with the center of rotating, it will cause a high intensity radial vibration at 1X (1x running frequency).

3.2 Misalignment

Misalignment is a condition where the centerlines of coupled shafts do not coincide. Vibration due to misalignment is usually characterized by 2X component and sometimes is 1X. The ratio of 1X to 2X component levels can be used as an indicator of severity. The key distinguishing feature is 2X component, and banana or eight orbit shape in some special situations.

3.3 Mechanical Looseness

Mechanical looseness usually involves mounts or bearing caps and almost always results in a large number of harmonics in the vibration spectrum. Looseness tends to produce vibration at 1X and 0.5X haft-order harmonics in the direction if the least stiffness.

3.4 Bearing defects

Rolling-elements bearings are the most common cause of machine failure. The dynamic performance of motor bearing is highly influential on the performance of the entire motor system. Faulty bearing can cause the system to function incorrectly, and cause vibration increase at some specific frequencies that result from bearing defects depend on the defect, the bearing geometry, and speed of rotation. These frequencies are fundamental cage frequency, ball pass outer raceway frequency, ball pass inner raceway frequency, and ball rotating frequency.

Ball pass outer raceway frequency f_{outer} appears when the rolling elements are not on the best road and can be calculated as :

$$f_{outer} = N_B f_c = N_B \frac{f_r}{2}\left(1 - \frac{D_b}{D_c}\cos\theta\right)$$

where N_B : number of balls or rollers

D_b : ball or roller diameter

D_c : cage diameter

θ : contact angle of bearing

f_r : rotating frequency

Ball pass inner raceway frequency f_{inner} appears when the shaft is not ideally circular :

$$f_{inner} = N_B (f_r - f_c) = N_B \frac{f_r}{2}\left(1 + \frac{D_b}{D_c}\cos\theta\right)$$

Ball rotating frequency f_b appears if a rolling element is not circular but has edges :

$$f_b == \frac{f_r}{2}\frac{D_c}{D_b}\left(1 - \frac{D_b^2}{D_c^2}\cos^2\theta\right)$$

Fundamental cage frequency f_c appears when one rolling element has larger or less diameter.

$$f_c == \frac{f_r}{2}\left(1 - \frac{D_b}{D_c}\cos\theta\right)$$

3.5 Electrical induced faults

Electrical faults are rotor problems, stator problems, phase unbalance, eccentricity. These faults produce vibration at 1X or 2 times of line frequency. The common feature is the amplitude will disappear when turn off the power.

When stator damage or phase unbalance appears, vibration will be produced at 2 times of line frequency. When rotor problems such as broken rotor bar or broken end-ring occurs , the 2 times of slip frequency component and sidebands occur.

3.6 Others

Oil whip, partial rub, crack shaft, and foundation distortion are another common induction motor failures. Oil whip is one of the easiest vibrations to recognize as it is one of those rare vibration with a frequency approximately 0.38X to 0.48X. Partial rub vibration usually appears at fraction of 1X, mostly at 1/2X. However, crack shaft and foundation distortion are difficult to identify. Crack shaft mostly produces vibration at 2X, and foundation distortion produces vibration that can be located at 1X, 2X, less than 1X, and sometimes at odd frequencies.

4. INDUCTION MOTOR DIAGNOSTIC SYSTEM

Decision tree is build in order to identify possible vibration causes in induction motor. Decision tree will analyze vibration signal, examine the predominant frequency of vibration, amplitude respond to speed variation, observe the direction of vibration, orbit of rotating, …. As indicated in previous part, each motor fault may generate vibration in its own unique way. Therefore, people usually perform vibration diagnosis using their experience and textbook knowledge.

This paper proposes a decision tree with 11 common causes of vibration (classes of decision tree) and 11 tests (attributes).

No.	Cause of vibration
1	Mechanical Unbalance
2	Misalignment
3	Partial rub
4	Crack
5	Mechanical Looseness
6	Ball bearing damage
7	Foundation distortion
8	Oil whip
9	Static air gap eccentricity or stator damage
10	Critical speed
11	Dynamic eccentricity air gap or rotor damage

Table 1 Cause of vibration

In order to identify these causes, special tests based on the predominant frequency are carried out. Table 2 describes these tests suggested in this paper :

No.	Test (attribute)	Value
1	What is the predominant frequency ?	1X, 2X, 1X and 2X, Harmonics of 1X (multiple),

		Higher than 1X, Lower than 1X
2	Is 0.38-0.48X component predominant ?	yes, no
3	Is bearing damage frequency predominant ?	yes, no
4	Is there $2f_{line}$ frequency ?	yes, no
5	Is there $2sf_{line}$ frequency ?	yes, no
6	Is there harmonics of 1/2X component ?	yes, no
7	Is amplitude change ?	yes, no
8	Is phase change ?	yes, no
9	Is axial amplitude larger than radial amplitude ?	yes, no
10	Is orbit shape leaning to banana or eight shape ?	yes, no
11	How is amplitude change during shut-down ?	constant, decrease, drop

Table 2 Decision tree test and its value

To generate the decision tree, it requires a set of samples for machine learning. After building a training set, C4.5 program now can create the decision tree. Table 3 shows the decision tree :

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Decision Tree:

Predominant frequency = 1x:
|   amplitude_change = yes:
|   |   2s_line frequency = yes: Dynamic air gap (4.6/0.0)
|   |   2s_line frequency = no: Partial rub (26.0/13.0)
|   amplitude_change = no:
|   |   bearing frequency = yes: Ball bearing damage (14.3/1.3)
|   |   bearing frequency = no:
|   |   |   2s_line frequency = yes: Dynamic air gap (8.4)
|   |   |   2s_line frequency = no:
|   |   |   |   0.38-0.48x = yes: Oil whip (3.7)
|   |   |   |   0.38-0.48x = no: Unbalance (30.0)
Predominant frequency = 2x:
|   Orbit shape = yes: Misalignment (50.0)
|   Orbit shape = no: Crack (50.0/20.0)
Predominant frequency = same:
|   Axial direction = yes: Misalignment (70.0)
|   Axial direction = no: Unbalance (30.0)
Predominant frequency = Multi:
|   Axial direction = yes:
|   |   Orbit shape = yes: Misalignment (30.0)
|   |   Orbit shape = no: Crack (4.5)
|   Axial direction = no:
|   |   amplitude_change = yes: Partial rub (14.9/1.9)
|   |   amplitude_change = no:
|   |   |   0.38-0.48x = yes: Oil whip (6.0)
|   |   |   0.38-0.48x = no: Looseness (44.6/6.6)
Predominant frequency = Higher:
|   bearing frequency = yes: Ball bearing damage (30.0)
|   bearing frequency = no:
|   |   amplitude_change = yes: Partial rub (10.0)
|   |   amplitude_change = no: Static air gap (30.0)
Predominant frequency = Lower:
|   0.38-0.48x = yes: Oil whip (25.0)
|   0.38-0.48x = no: Partial rub (35.0/15.0)
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Table 3 Decision Tree for motor diagnosis

From this tree, vibration causes can be predicted, the result will depend on the reliability and accuracy of input data. For example, if the predominant frequency of vibration signal is 1X, there is not $2sf_{line}$ component, and 1X amplitude is not change, the tree will give the decision that the motor problem probably is unbalance (probability is 0.63), or ball bearing damage (0.27), or oil whip (0.1).

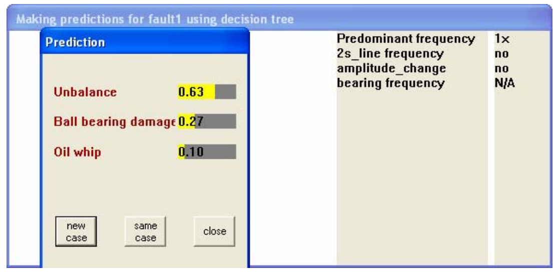

Figure 1 : Predicted result of decision tree

The decision strongly depends on amount of data. In above case, if bearing damage frequencies are provided, the result will become more accurate.

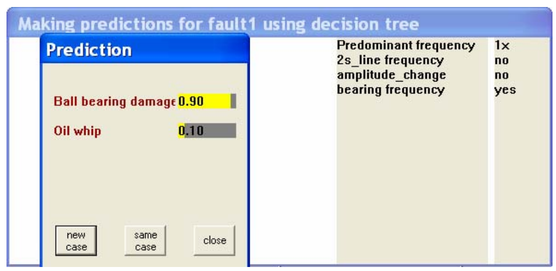

Figure 2 : Predicted result of decision tree Ball bearing damage (0.9) and Oil whip (0.1)

5. CONCLUSION

This paper proposes an efficient way to monitor and diagnose induction motor, knowledge and experience are collected and classified in order to build a diagnostic system. Decision tree has the ability to predict the motor condition in the same way as that of an expert in this field.

On-going research is being carried out in decision tree, especially in experiment direction.

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