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Fuzzy Diagnosis of Turbomachines
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Abstract— This paper presents a fuzzy knowledge-based system for turbomachinery diagnosis. Given symptoms associated with a vibration problem, the system can identify and rank possible causes by performing incremental forward chaining. The diagnostic system incorporates an attribute weighting component to reflect the relative significance of conditional attributes, thereby allowing the system to produce more accurate diagnoses. The ability of this system to identify causes of typical vibration problems in rotating machinery is supported with tests on real cases.

I. INTRODUCTION

The success of many industrial plants depends on the continued and safe operation of their rotating machinery. Shutting down a machine for repair can be a very expensive business [11]. A fast and reliable diagnosis is, therefore, required whenever a vibration problem occurs so that the actual cause can be identified and fixed as soon as possible. An early diagnosis helps to avoid extensive damage to the machine and hence to reduce the downtime for repair. Yet, diagnosing vibration problems in turbomachinery requires substantial domain specific knowledge. With modern machinery becoming more and more complex and diagnostic knowledge becoming more and more difficult to possess by ordinary field operators, the need becomes more and more pressing for a computer-based solution or a knowledge-based system for turbomachinery diagnosis.

Uncertainty permeates the way of problem solving in the real world, however. The domain expertise in turbomachinery diagnosis involves considerable constituents of uncertain knowledge. This usually includes vague concepts, such as "high" in the proposition "if the vibration at twice running speed is high, then the cause is misalignment", and undeterministic choices, such as "either thrust bearing damage or temporary rotor bow may cause the predominant frequency to become high". Thus, the reliability of a turbomachinery diagnostic system relies upon its ability of reasoning under uncertain situations.

Fortunately, there exist many techniques useful for copying with uncertainty in knowledge-based systems. In particular, fuzzy systems have proved to be an effective tool for representing and reasoning about vague knowledge. This is rooted in their use of fuzzy logic as the mathematical foundation in providing a natural framework for uncertainty management. This is, in turn, because fuzzy representation allows everything to be, though need not be, a matter of degree. Unlike conventional logics, the transition from one concept to another in fuzzy logic is gradual, rather than abrupt. This helps reduce the difficulty in encoding imprecise or incomplete knowledge typically employed in a knowledge-based system, and allows a possibly inexact conclusion to be inferred from inexact premises. Inspired by these observations, this paper presents

a successful application of fuzzy systems in implementing an automated diagnostic tool for identification of vibration causes in turbomachines.

The rest of the paper is organised as follows. To be complete, a brief introduction to the conventional turbomachinery diagnosis is first given in section II. A detailed account of the requirements and design of the fuzzy rule-based diagnostic system is then presented in section III. To demonstrate the effectiveness of the system, the results of typical experiments on real cases are reported in section IV. Finally, the paper is concluded in section V, with future directions of research pointed out.

II. TURBOMACHINERY DIAGNOSIS

Turbomachinery include gas turbines, turbocompressors, steam turbines, etc. It is natural for machines to have vibrations, in terms of motions of a machine or machine part back and forth from its rest position. However, if the vibration of a machine becomes excessive, some mechanical fault is usually the reason. As indicated in [11], for typical rotating machines, there may exist over 30 possible causes for machine vibration, such as initial unbalance, temporary rotor bow, misalignment, bearing damage, etc. and 88 different possible symptoms that can be classified into the following 10 symptom categories:

- predominant frequency of vibration
- direction of predominant amplitude of vibration
- location of predominant amplitude of vibration
- amplitude response to speed increase
- amplitude response to speed decrease
- predominant sound of vibration
- effect of operating conditions
- effect of oil pressure, temperature and flow
- history of machine
- damage or distress signal

For simplicity, throughout this paper a symptom category is simply referred to as a symptom (which can have different values) unless otherwise stated.

Traditionally, people working with turbomachinery usually perform vibration diagnosis using their field experience and textbook knowledge. One popular tool for turbomachinery diagnosis is Sohre's charts given in [11], developed by a professional turbomachinery consultant. The charts relate the subjective probability of the occurrence of a symptom to an underlying cause. For example, look at a small part of the charts as shown in figure 1, when "misalignment" is found to be the cause of a vibration problem, the probabilities of the occurrence of the predominant frequencies 1/2xRPM, 1xRPM and 2xRPM are 0, 0.3 and 0.6 respectively, where RPM stands for revolution per minute, a unit for rotations frequency (and x is simply a connective notation, e.g. 2xRPM means

2 revolution per minute). In light of the popularity of these charts, they are used as the major source of domain knowledge required by the diagnostic system to be presented below.

Causes of vibration	rotor and stator resonant frequency	40-59% oil whirl frequency	50-100% oil whirl frequency	1 x running frequency	2 x running frequency	higher multiple	1/2 running frequency	1/4 running frequency	lower multiple	odd frequency	very high frequency
initial unbalance	5			90	5	5					
permanent bow or lost	30			90	5	5					
temp. rotor bow	20			90	5	5					
casing distortion	10	10	10	60	20	10					
foundation distortion		20		40	20					10	
seal rub	10	10	10	20	10	10			10	10	10
rotor rub. axial	20	20	20	30	10	10			10	10	10
misalignment	5	10		30	60	10					10
piping forces	5	10		30	60	10					10

Predominant Frequency of Vibration

Fig. 1.   Predominant frequency symptoms vs. vibration causes

Having recognised the significance of applying knowledge-based techniques to help finding faults in turbomachines, there have been many such diagnostic systems developed in the literature. For example, the work of [15], [16] provided an initial expert system architecture for health monitoring and vibration based diagnosis of turbomachinery. In this research, diagnosis is based on a combination of general fault matrix analysis, machine specific experience, symbolic modelling and computer simulation. A similar approach is more recently reported in [17], supported with full implementation. This system aims at aiding plant operators in diagnosing the cause of abnormal vibration for rotating machinery. Again, a decision table based on the cause-symptom matrix is used as a probabilistic method for diagnosing abnormal vibration. In addition, decision-tree based inductive learning [6] is adopted to obtain and represent diagnostic knowledge in a structured format.

There have been alternative approaches to conventional expert systems for monitoring and diagnosis of turbomachines. For instance, while treating diagnosis as a pattern classification task and based on the vibration characteristic spectrum, the approach proposed in [3] exploits the rough set theory [9] to facilitate diagnoses. In particular, it obtains accurate diagnostic results directly from a set of complete fault spectrum samples, and satisfactory diagnostic results from a set of incomplete fault spectrum samples. Also based on rough sets, a method for steam turbine-generator vibration fault diagnosis was proposed in [8]. This work applies the rough attribute reduction algorithm [13] to select the key features that will have the most significant impact upon the classification process in order to perform diagnosis.

Systems developed following all aforementioned research have enjoyed much success in real-world applications. Yet, neither of these has addressed the type of uncertain knowledge that is considered in this paper. Thus, the work described herein forms a useful complementary approach to automated monitoring and diagnosis of turbomachines.

III. THE APPROACH

A. System Requirements

The task of the fuzzy knowledge-based system introduced herein is to determine possible causes of a vibration problem and rank them according to their possibilities incrementally. In particular, the system is required to produce an intermediate diagnostic result for each symptom presented by the user. Otherwise, it could be tedious, or of little use, if the system had to await the user to present all observed symptoms before generating some hypotheses.

In general, basic vibration characteristics are very useful in performing diagnosis on rotating machines [5]. The system to build should therefore, first allow the user to provide input of whether any of such symptoms is observed from the machine under diagnosis. In practice, most of the possible causes can be eliminated after important vibration symptoms have been presented, and so there are normally not many causes under investigation which would require observations of other types of symptom. Given each symptom, the system should generate currently possible causes. The user can then decide whether or not to continue the diagnostic process. This decision point has shown to be helpful in diagnosis as the user may already be able to guess what to check given only the partial diagnostic result.

The system should also be able to provide a what-if analysis facility, in order to help the user to investigate the impacts of potentially different symptoms upon the diagnostic result. At the end of a consultation, the user should be allowed to change any of the given symptoms to see if there are alternative symptoms which may affect the diagnoses significantly. In so doing, the reliability of the diagnoses can be examined and the diagnostic results may be revised (if necessary).

B. Knowledge Representation

The domain knowledge extracted from Sohre's charts is represented in a set of symptom-cause diagnostic rules; many of which are used to deduce causes with given symptoms, whilst some of which are used to eliminate a certain cause given a particular symptom. The latter type of rules are acquired from those parts of the charts where no possible link exists between a given symptom and a certain cause, in order to ensure full coverage of possible associations between conditional attributes and conclusions. The rules used for diagnostic deduction are of the following general form:

If Symptom is A then Cause is B

Based on a careful analysis of the domain knowledge, two types of symptom can be identified:

- Crisp symptoms: Symptoms whose values are precise, such as the location of predominant amplitude.
- Fuzzy symptoms: Symptoms whose values are imprecise or vague, such as the direction of predominant amplitude of vibration.

For crisp symptoms, they can be easily represented as variables taking precisely defined (symbolic) values. A fuzzy symptom is, however, represented as a linguistic variable

taking fuzzy values defined on its underlying universe of discourse. As an example, the symptom of direction of predominant amplitude is fuzzy because its possible values "vertical", "horizontal" and "axial" are vaguely defined concepts. The transition from one direction to another is not abrupt but gradual. These values may be defined as fuzzy sets as shown in figure 2, where V stands for "vertical", H for "horizontal" and A for "axial". The three dimensional nature of the direction is herein simplified into two dimensional, without altering their underlying relationships.
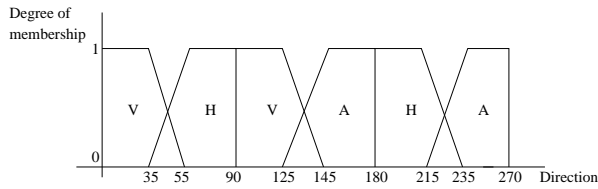

Fig. 2.   Fuzzy sets for the direction of predominant amplitude of vibration

Another interesting example is to represent the values of the symptom conveyed by the predominant frequency of vibration. The possible values of this symptom are 1/2xRPM, 1xRPM, 2xRPM, etc. These symbolic values are themselves precisely defined, with exact boundaries between them. Unfortunately, it is difficult for the user to tell exactly if a particular vibration frequency is predominant with regard to its amplitude. Figure 3 shows a typical vibration amplitude vs. frequency plot. It can be seen from the plot that apart from the two significant predominant frequencies "oil whirl" and "1xRPM", there exists another less significant, but still important frequency. This frequency may be an indication of some potential fault and hence should be considered also.
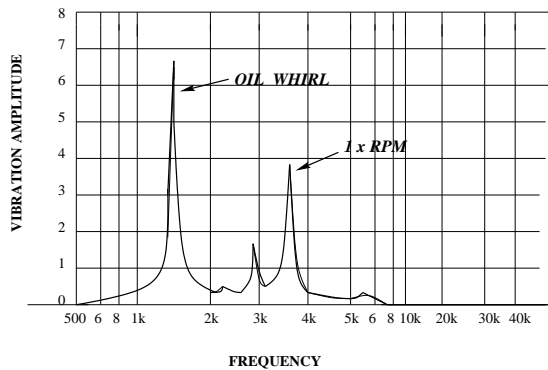

Fig. 3.   Vibration amplitude vs. frequency plot

It is, however, not practical to use a numerical threshold to decide whether the amplitude of a frequency is high enough to be considered predominant, as the amplitudes of frequencies vary in different machines. A frequency with a height of 80% of the maximum in one machine may be equivalent to that of 50% in another. In practice, therefore, the amplitudes of a frequency are usually described in one of the three elastic linguistic terms "high", "close to limit" and "low", generally suitable for different machines. As commonly assumed in turbomachinery diagnosis, by setting the limit to around 20%

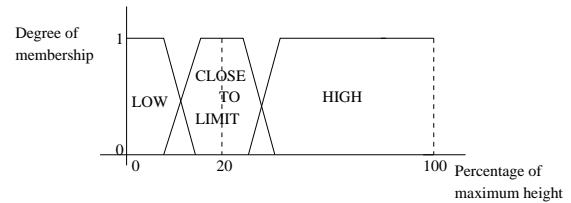of the maximum height, these terms may be represented by the fuzzy sets shown in figure 4.

Fig. 4.   Fuzzy sets for the terms "high", "close to limit" and "low" in the description of vibration amplitudes

With regard to the two different types of symptom, the diagnostic rules are also classified into two types: crisp-crisp rules and fuzzy-crisp rules. The knowledge base directly extracted from Sohre's charts therefore consists of a collection of diagnostic rules belonging to either of these two types, plus those rules used to eliminate impossible causes. In particular, a crisp-crisp rule is one whose condition and conclusion are both crisp propositions. For example,

> If location of predominant amplitude is shaft
> then possible cause is initial unbalance

A fuzzy-crisp rule, on the other hand, is one whose condition is a fuzzy proposition whilst whose conclusion is a crisp proposition. For example,

> If direction of predominant amplitude is axial
> then possible cause is initial unbalance

and

> If predominant frequency is 1xRPM (high)
> then possible cause is initial unbalance

Incidentally, in the last example, 1xRPM (high) means that the frequency 1xRPM is predominant with its amplitude considered to be high.

C. Weighting of Conditional Attributes and Rules

The directly extracted rules are however, obtained by treating different symptoms equally. In reality, different conditional attributes may have very different effects upon the derivation of a conclusion. This is of particular importance for the diagnostic problem at hand, where a closer investigation into the rules reveals that many of them may have the same conclusion while having rather different conditions. Thus, a method that would allow the reflection of the relative significance of the different symptoms in relation to the same possible underlying cause is highly desirable.

Fortunately, in monitoring and diagnosing rotating machines a good number of useful past cases have been collected. This allows for the estimation of the relative degrees of dependency of a conclusion upon a given conditional attribute. Note that such derived if-then rules are actually acausal in describing the underlying relationships between symptoms and causes. This is because a real cause-effect relation only makes sense the other way round, with the conditions (i.e. the symptoms) depending upon the conclusion (i.e. the cause).

Computationally, the estimation of the dependency degrees is a fairly straightforward task because the fuzzy symptom-cause rules directly derived from the Sohre's charts are generally relating only one symptom to a possible cause. Thus, the relative (acausal) dependency degree of a conclusion upon a condition can be estimated via counting the number of times of those past cases where the found cause did lead to the observed symptom and that of the total past cases where the same cause led to all of those different observed symptoms. The quotient resulting from dividing the first count by the second is the weight associated with the rule that links that specific condition with the given conclusion.

Formally, given a set of K directly derived rules of the form

$$R_j: \quad \text{If Symptom is } A_j \text{ then Cause is } B, \quad j = 1, 2, ..., K$$

the relative degree of dependency of B upon A_i is:

$$W_{R_j}(B, A_j) = \frac{\alpha_{A_j}}{\sum_{i=1}^{K} \alpha_{A_i}}, \quad j \in \{1, 2, ..., K\}$$

where α_{A_i} stands for the count of the number of times in which attribute $A_i, i = 1, 2, ..., K$ is associated with the conclusion B.

For simplicity, in the following presentation, such an estimated rule weight is denoted by W_j unless otherwise stated. In so doing, each of those directly derived rules will then be attached with a rule weight and represented as follows:

$$R_j: \quad \text{If Symptom is } A_j \text{ then Cause is } B \quad (W_j)$$

It is this kind of rules that are actually used to implement the diagnostic system.

In addition to the above weighting scheme for individual rules, to facilitate the capturing of the significance possibly established with an observation or with a conclusion, every quantity is hereafter also attached with a weight. More details on this will be given below.

D. Reasoning Method

The basic inference method used in the fuzzy knowledge-based diagnostic system is forward chaining. Namely, the search for solution starts from given evidence to see how far the conclusions can be pushed via executing the rules in the knowledge base. Forward chaining is adopted because most of the facts about a vibration problem are given initially and as many as possible causes should be considered. Given the observation of a symptom, rules with their conditions satisfied by that piece of evidence (or fact) will be applied so that possible causes are deduced and definitely impossible ones eliminated.

During a consultation of the system, a crisp-crisp rule is applied only when its condition exactly matches the given fact, whilst a fuzzy-crisp rule is fired so long as the fuzzy set associated with its condition has some degree of overlap with the fuzzy set associated with that fact. The intuition behind the way of firing a fuzzy-crisp rule is the following: Given that both the value of the conditional attribute and that of the fact are both represented by fuzzy sets in general (which are defined on the same universe of discourse), the degree of overlap between these two fuzzy sets reflects the similarity between them and hence the similarity between the condition and the fact.

In this paper, the technique reported in [1] is used to measure fuzzy set similarity. This measure of similarity S is based upon the measure of possibility P and that of necessity N. Given the fuzzy set associated with the condition, F_c, and the fuzzy set associated with the fact, F_f, the measure of similarity S is defined by

$$S = \begin{cases} P(F_c|F_f), & N(F_c|F_f) > 0.5 \\ (N(F_c|F_f) + 0.5) \times P(F_c|F_f), & \text{else} \end{cases}$$

where

$$P(F_c|F_f) = max(min(\mu_{F_c}(u), \mu_{F_f}(u))), \forall u \in U$$

(with U being the universe of discourse) and the measure of necessity N is defined by

$$N(F_c|F_f) = 1 - P(\neg F_c|F_f)$$

When firing a crisp-crisp rule the weight of the conclusion is then calculated as follows:

$$W_{conclusion} = W_{fact} \times W_{rule}$$

By analogy, the weight of the conclusion of a fuzzy-crisp rule when fired is calculated as follows:

$$W_{conclusion} = W_{fact} \times W_{rule} \times S$$

where W_{fact} and W_{rule} have the obvious meanings of being the weight associated with the fact and that with the rule fired, respectively.

This approach captures the intuition well: The higher the value of S, the more similar the fact to the condition value, and so the higher the weight of the conclusion. In particular, if the fuzzy set of the conditional attribute and that of the fact are identical, S will be equal to 1 and $W_{conclusion} = W_{fact} \times W_{rule}$.

If a deduced conclusion already exists, its weight is updated by the following:

$$W_{conclusion} = W_{new} + W_{old} - W_{new} \times W_{old}$$

This once again reflects the intuition in that the more evidence there exists which supports a conclusion, the higher is the significance of that conclusion. Indeed, the weight of a fact lies in the interval [0, 1]. In the present work, the threshold for rule firing is set to zero so that all symptoms can be considered no matter how low their weights are (though this threshold can be easily reset should a higher value be preferred in order to increase the diagnostic efficiency of the system).

As an example, consider the following rules:

R_1 If direction of predominant amplitude is vertical
then possible cause is misalignment ($W = 0.2$)

R_2 If direction of predominant amplitude is horizontal
then possible cause is misalignment ($W = 0.3$)

R_3 If location of predominant amplitude is shaft
then possible cause is misalignment ($W = 0.3$)

R_4 If location of predominant amplitude is casing
then possible cause is misalignment ($W = 0.2$)

Rules R_1 and R_2 are fuzzy-crisp rules whilst rules R_3 and R_4 are crisp-crisp rules. Suppose that the values of "direction of predominant amplitude" are represented by the fuzzy sets as shown in figure 2 and that the following facts are given by the user:

a. location of predominant amplitude is shaft ($W = 1$)
b. direction of predominant amplitude is vertical ($W = 1$)

Following the method described above, rule R_3 is fired and the weight of the conclusion "possible cause is misalignment", W_1, is equal to $1.0 \times 0.3 = 0.3$. Rule R_1 is also fired because the fuzzy set associated with its condition and that with the fact a are the same, both being "vertical". In this case, S is equal to 1 and the weight of the conclusion, W_2, is equal to $1.0 \times 0.2 \times 1.0 = 0.2$. Since the conclusion already exists, its new weight W_3 is calculated as follows:

$$W_3 = W_1 + W_2 - W_1 \times W_2$$
$$= 0.3 + 0.2 - 0.3 \times 0.2$$
$$= 0.44$$

Because the fuzzy sets denoting the values "vertical" and "horizontal" have some degree of overlap, rule R_2 also fires. Suppose that the degree of similarity S between the two fuzzy sets is calculated to be 0.1. The weight W_4 of the conclusion obtained from firing rule R_2 is then equal to $1.0 \times 0.3 \times 0.1 = 0.03$. This new weight is again combined with the existing W_3 to update the weight of the same conclusion such that

$$W_5 = W_3 + W_4 - W_3 \times W_4 = 0.46$$

Clearly, with the accumulation of evidence partially supporting a conclusion the weight of this conclusion will be (correctly) increased.

In addition to allowing partial matching between rule conditions and given facts, the utilisation of fuzzy logic allows the user to have a good flexibility in providing inputs to the system. For example, suppose that the fuzzy sets representing the values "vertical", "horizontal" and "axial" as shown in figure 2 are denoted by $F_{vertical}$, $F_{horizontal}$ and $F_{vertical}$ respectively. If the user indicates that the value of the direction of predominant amplitude is "vertical or horizontal", this value can be easily represented by the fuzzy set $F_{vertical} \cup F_{horizontal}$. In this case, given the fact that

"direction of predominant amplitude is vertical or horizontal",

the first two rules provided above will be fired. The weight of the conclusion due to firing rule R_1 is calculated based on the degree of overlap between $F_{vertical} \cup F_{horizontal}$ and $F_{vertical}$, and that due to rule R_2 is computed based on the degree of overlap between $F_{vertical} \cup F_{horizontal}$ and $F_{horizontal}$. Furthermore, the user can give qualified uncertain inputs using fuzzy hedges [2], [4] such as "extremely", "very" and "quite" to indicate the detail of information and hence, to allow more accurate diagnoses to be generated.

IV. EXPERIMENTAL RESULTS

The performance of this system, implemented in Fuzzy-CLIPS [7], has been verified with a number of real cases. The results of two typical case studies are presented here.

Before going on, it is worth noting that the diagnostic system has a threshold for returning ranked possible causes which can be set by the user. This is merely for use in reporting diagnostic results and should not be confused with the threshold of an internal weight for rule firing (which is set to zero as indicated previously). Only those causes found whose weights are larger than the set threshold are reported to the user. This facility allows the user to concentrate on important diagnoses only. In both experimental cases below, the threshold is set to 0.5.

A. Case I

The actual underlying cause of this case is "oil whirl" and the symptoms observed are:

(a) predominant frequency of vibration: 40-50% (high)
(b) direction of predominant amplitude: vertical
(c) location of predominant amplitude: shaft
(d) amplitude response to speed increase: coming suddenly
(e) amplitude response to speed decrease: dropping out suddenly
(f) predominant sound of vibration: low frequency rumble

As mentioned earlier, the system performs diagnosis incrementally with respect to each symptom presented by the user. After the "predominant frequency" symptom is given, the intermediate result is shown as follows:

```
 The following causes are possible:
(Numbers in brackets indicate their
possibilities.)
  1. thrust bearing damage (0.91)
  2. bearing and support excited vibration (oil
     whirls, etc.) (0.64)
>> Do you want to continue the diagnosis?
yes/no:
```

As can be seen, in response to the initial symptom given, only two possible causes are found and one of them is the actual cause "oil whirl". Now the user can continue the diagnosis to volunteer more symptoms observed. Given another symptom, "direction of predominant amplitude", the new intermediate result generated by the system is shown as follows:

```
 The following causes are possible:
(Numbers in brackets indicate their
possibilities.)
  1. thrust bearing damage (0.94)
  2. bearing and support excited vibration (oil
     whirls, etc.) (0.81)
  3. foundation distortion (0.6)
  4. bearing damage (0.55)
  5. rotor rub axial (0.55)
  6. casing distortion (permanent) (0.55)
  7. casing distortion (temporary) (0.55)
>> Do you want to continue the diagnosis?
yes/no:
```

Although five more causes are found to be possible, the weight of "oil whirl" has increased to 0.81. The final result

generated by the system after all the symptoms available have been presented is given below:

```
 SYMPTOM(S):
 1. Predominant frequency of vibration:
    40-50% oil whirl frequency (high)
 2. Direction of predominant amplitude:
    vertical
 3. Location of predominant amplitude:
    shaft
 4. Amplitude response to speed increase:
    coming suddenly
 5. Amplitude response to speed decrease:
    dropping out suddenly
 6. Predominant sound of vibration:
    low frequency rumble
POSSIBLE CAUSE(S):
 1. bearing and support excited vibration (oil
    whirls, etc.) (1.0)
 2. thrust bearing damage (0.99)
 3. casing distortion (temporary) (0.97)
 4. rotor rub axial (0.94)
 5. bearing damage (0.93)
 6. seal rub (0.87)
 7. piping forces (0.82)
>> Do you want to perform what-if analysis on
>> the result?
yes/no:
```

From this result, it is clear that the underlying cause "oil whirl" is ranked the top and has the highest significance weight of 1. However, given limited observations and a knowledge base manually derived from *ad hoc* charts, some causes other than "oil whirl" are also found to have a very high weight such as "thrust bearing damage". Yet, an important task of the system is to rank possible causes so that the user can know which ones are important and should be checked. Therefore, if possible, those causes with a very high weight value should be checked as well as "oil whirl".

The system allows the user to perform what-if analysis and, hence, to study the possible impact of changes of any given symptoms upon the diagnostic result. With the help of the what-if analysis facility, when the predominant frequency is changed for instance to 1xRPM (high) in the above example, the updated diagnoses can be generated as presented below (without the need of starting a new consultation from the beginning):

```
 SYMPTOM(S):
 1. Predominant frequency of vibration:
    1xRPM (high)
 2. Direction of predominant amplitude:
    vertical
 3. Location of predominant amplitude:
    shaft
 4. Amplitude response to speed increase:
    coming suddenly
 5. Amplitude response to speed decrease:
    dropping out suddenly
 6. Predominant sound of vibration:
    low frequency rumble
POSSIBLE CAUSE(S):
 1. temporary rotor bow (1.0)
```

```
 2. thrust bearing damage (0.99)
 3. casing distortion (temporary) (0.99)
 4. bearing damage (0.95)
 5. rotor rub axial (0.95)
 6. seal rub (0.88)
 7. piping forces (0.86)
>> Continue what-if analysis?
yes/no:
```

This result is quite different from what was shown earlier. "Oil whirl" has been correctly eliminated and the most likely cause becomes "temporary rotor bow", which was not even present before. This updated, most likely cause is indeed the one for the amplitude of the frequency 1xRPM to become high.

B. Case II

In this case, the actual underlying cause is "thrust bearing damage", and the symptoms observed are:
(a) predominant frequency of vibration: 1xRPM (high) and 2xRPM (high)
(b) direction of predominant amplitude: horizontal
(c) location of predominant amplitude: shaft
(d) amplitude response to speed increase: increase
(e) amplitude response to speed decrease: decrease
(f) predominant sound of vibration: loud roar

Similar to case I, when the user inputs the symptoms one by one, the system generates intermediate diagnoses accordingly. Instead of repeating a similar consultation process, the final diagnostic result produced by the system is presented here:

```
 SYMPTOM(S):
 1. Predominant frequency of vibration:
    1xRPM (high), 2xRPM (high)
 2. Direction of predominant amplitude:
    horizontal
 3. Location of predominant amplitude:
    shaft
 4. Amplitude response to speed increase:
    increases
 5. Amplitude response to speed decrease:
    decreases
 6. Predominant sound of vibration:
    loud roar
POSSIBLE CAUSE(S):
 1. thrust bearing damage (1.0)
 2. journal and bearing eccentricity (1.0)
 3. foundation distortion (1.0)
 4. casing distortion (permanent) (1.0)
 5. casing distortion (temporary) (1.0)
 6. temporary rotor bow (1.0)
 7. permanent bow or lost rotor parts (1.0)
 8. initial unbalance (1.0)
 9. bearing damage (0.99)
10. seal rub (0.99)
11. piping forces (0.98)
12. misalignment (0.98)
13. rotor rub. axial (0.98)
>> Do you want to perform what-if analysis on
>> the result?
yes/no:
```

In this case, the knowledge-based system identifies 13 possible causes, each having a very high significance weight.

V. CONCLUSIONS AND FURTHER WORK

This paper has presented a fuzzy system for turbomachinery diagnosis, which combines fuzzy logic and weight approaches for representing and reasoning about domain specific knowledge. According to the results of experiments carried out so far, the diagnostic system can identify the underlying cause(s) of a real problem. As with any fuzzy rule-based system, where the system's knowledge is induced from given examples, the applicability of this diagnostic system can be expected when used to help finding faults of experienced nature. However, it should not be expected for the proposed system to work universally well for any situations, especially for the situations where unseen faults may occur.

In fact, the current approach relies upon the assumption that a full coverage of symptom-cause associations can be extracted from Sohre's charts. Although this may be the case for commonly applied rotating machines, knowledge regarding certain new types of machine may not be complete. For effective diagnosis the natural next step in improving this system is to include a mode of unknown cause. Such a revision to the system will require (a) the introduction of a rule concluding on an unexperienced fault for each category of possible symptom that full-coverage is not guaranteed, and (b) the recalculation of the weights of all the relevant rules. Alternatively, the ideas of applying qualitative model-based reasoning, as per the Tiger system that is presented in [14], may be borrowed to address this problem.

It is also worth noting that the second example given in the experimental studies reveals an important limitation of the current system: Although the actual cause "thrust bearing damage" is ranked the top, there are 7 other causes found to have a weight of 1. Albeit multiple causes for vibration may be common in rotating machines, there would not normally exist so many of them at the same time. Further investigations into how to reduce the number of returned faults are needed. Nevertheless, this does not affect the usefulness of the present system, since what the user often requires is typically a piece of advice of what might be the possible causes for the observed symptoms.

Finally, the present computation mechanism for the rule weights is rather simplistic. There are other alternatives that may be employed, including the use of measures of entropy [10], rough dependency [9] and fuzzy-rough dependency [12]. This remains an interesting future investigation.

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