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TABLE OF CONTENTS

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An Uncertainty Reasoning Model for Synergistic Diagnosis

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Abstract

To secure reliable plant operation, it is necessary to provide a predictive maintenance system. Even though there are several failure diagnosis methods available, they are not precise and their diagnosis is incomplete and uncertain. In this paper, to accommodate uncertain information from multiple diagnosis methods, an evidence theory-based synegistic diagnosis model is proposed. This model is based on Dempster-Shafer theory for individual evidence calculation and evidence combination for given hypotheses; namely, failure types. An application example for turbine generator diagnosis is presented based on the proposed synergistic diagnosis model, and a practical implementation for actual turbine generator plant diagnosis is also suggested.

Key Words: Uncertainty reasoning, synergistic diagnosis, evidence combination.

1 Introduction

A reliable and easy maintainable plant is essential to stable production and economic efficiency. The economic efficiency of a plant, whether it produces electricity or commodities, will depend on reliable operation of the production systems. However, a reliable plant cannot be achieved without proper failure detection and diagnosis that lead to efficient and optimal preventive maintenance. There are many methods which diagnose abnormal plant conditions, and each method usually considers and focuses on only one parameter for early detection of failures [9, 10]. The main reason that a diagnosis method fails is that its performance varies considerably with surrounding conditions and does not adapt with changing conditions.

For example, power plant facilities are very complex in structure and have various failure factors, yet their diagnosis methods are unsatisfactory except under controlled and ideal conditions. Even though research intensified on incipient plant failure detection, no single diagnosis method can detect the majority of failures. However, an intelligent combination of diagnosis methods may be a reasonable solution for better and precise diagnosis of plant failures [7].

In a synergistic diagnosis, probabilistic or "degree of belief" outcomes of the diagnosis methods are combined to produce a higher degree of belief. The "method" here is not restricted to computer software or instruments, but could include a human expert in plant diagnosis.

This paper provides a formal framework to implement a combined set of diagnosis methods into a synergistic diagnosis by applying uncertainty reasoning. The evidence theory of Dempster-Shafer on uncertainty and evidence is utilized to combine several different diagnosis methods and their uncertain diagnostic results. Based on their independent observation, we assume that the diagnosis methods produce, their belief level on a certain type of failure as a number between 0.0 and 1.0; 0.0 for the lowest level and 1.0 the highest level. It then combines these degrees on failure types to reach a combined evidence on failure types. We also provide a plant diagnosis model suitable for practical applications. In the next section we discuss the Dempster-Schafer theory of combination and, later, the proposed synergistic model, followed by its application to plant diagnosis.

2 Dempster-Shafer Theory of Uncertainty Reasoning

2.1 Incomplete Knowledge and Uncertainty Reasoning

One of the many difficulties associated with the development of an intelligent diagnosis system is the fact that the information from each diagnosis method contains considerable uncertainty. Furthermore, the behavior of failures is not consistent. Similar conditions can bring out different failure characteristics and symptoms. Sometimes the behavior of failure can be very similar to the phenomenon of the normal transient or temporary events. Above all, plant failures are quite complicated, and it is extremely difficult to obtain complete knowledge and information about failure types and characteristics.

Hence, we seek a system that makes it possible to form an optimal and highly reliable diagnosis by utilizing incomplete knowledge and information [8]. To accommodate uncertainty, an intelligent and synergistic diagnosis system must have some way of calculating its confidence level in a conclusion by the proportion of the certainty level of the evidence. The most widely used representation of uncertainty has been in terms of

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a probability distribution which has a firm mathematical basis. However, many situations do not lend themselves to such convenient treatment, and require special approaches [2]. One widely used approach to tackle uncertain outcomes is to substitute an equivalent *certain* system for an *uncertain* system. This *engineering approach* to uncertainty is simply to avoid explicit representation of and reasoning with uncertainty. Most AI programs engineer uncertainty out of the task domain to some extent. The potential problem with this approach is that one may lose a valuable source of constraints. This is especially the case when it is uncertain how to use available information [3].

The Dempster-Shafer evidence theory, like Bayesian theory, relies on degrees of belief to represent uncertainty [6]. However, unlike Bayesian theory, it permits one to assign degrees of belief to subsets of hypotheses. In Bayesian theory one constructs a probability distribution over all individual singleton hypotheses, but in evidence theory a distribution is constructed over all subsets of hypotheses. In addition, for the evidence-gathering process in synergistic diagnosis with multiple diagnosis methods, Dempster-Shafer's evidence combination rule provides a formal proposal to meet the requirement of a solid way of combining the support for a hypothesis, or for its negation, based on multiple, accumulated outputs from the diagnosis methods.

2.2 Basic Belief and Belief Function

Dempster-Shafer theory uses a number in the range [0, 1] to indicate belief in a hypothesis given evidence. This number is the degree to which the evidence supports the hypothesis. The impact of each distinct piece of evidence on a subset of *frame of discernment*, denoted by Θ, which are all the cases of failure cause or type, is represented by a variable m called a *basic belief*. The quantity $m(\alpha)$ is a measure of that portion of the total belief committed exactly to α, where α is an element or a set of elements of Θ. This portion of belief cannot be further subdivided among the subsets of α and, thus, does not include portions of belief committed to subsets of α.

For example, in a diagnosis problem assume that there are three failure types to be identified: A, B, and C. Imagine field information over a given time period, and a hypothesis about the failure type. In addition to the three singleton hypotheses (namely α could be A, B, or C), there may be other hypotheses such as U (Unknown) failure, which indicates that system may be under A or B or C (namely, $\alpha=\{A, B, C\}$), or "Non A" type, which indicates either B or C type (namely, $\alpha=\{B, C\}$), etc.

Suppose the evidence that the probability (b) of A or B is 0.6 is obtained as $b_{\alpha=\{A,B\}}=0.6$. In the evidence theory it is possible to assign the probability 0.6 to the set $\{A, B\}$ without committing any of that 0.6 to either member of the set. In the Bayesian approach it would be natural to artificially divide the 0.6 among A and B. Furthermore, in the Bayesian scheme, we assign the remaining 1 - 0.6 = 0.4 of the probability distribution to C. In contrast, evidence theory approach assigns the remaining 0.4 to the set $\{A, B, C\}$, that is, to the set that reflects ignorance of system status.

Clearly, it would be useful to define a function that computes a total degree of belief in α. This quantity would include not only belief committed exactly to α but also belief assigned to all subsets of α. Such a function is called a *belief function* and represented by *Bel*. In Dempster-Shafer theory, a belief function is the sum of the basic beliefs assigned exactly to every subset of α by m. Therefore, for $\alpha=\{A, B, C\}$, the belief function for this specific hypothesis includes the basic beliefs of all the subsets of the hypothesis as indicated below:

$$Bel(A, B, C) = m(A, B, C) + m(A, B) + m(B, C) + m(A, C) + m(A) + m(B) + m(C). \quad (1)$$

Thus, $Bel(\alpha)$ is a measure of the total degree of belief in α and not of the amount committed precisely to α by the evidence giving rise to m. $Bel(\Theta)$ is always equal to 1 since $Bel(\Theta)$ is the sum of the values of m for every subset of Θ.

2.3 Combination of Belief Functions

Reasoning with the total degree of belief on a hypothesis generated by multiple methods requires a combination of belief functions derived from basic beliefs. Let Bel_1 and Bel_2 and m_1 and m_2 denote two belief functions and basic beliefs from two diagnosis methods 1 and 2, respectively. And suppose that for a given system one method supports failure type A or B to degree 0.6 (that is, $m_1\{A, B\}=0.6$) whereas another rejects failure type A to degree 0.7. The belief of the second method can be expressed by $m_2\{\sim A\} = m_2\{B, C\} = 0.7$.

Dempster's rule computes a new basic belief, denoted $m_1 \oplus m_2$, which represents the combined effect of m_1 and m_2. The corresponding belief function, denoted $Bel_1 \oplus Bel_2$, is then obtained from $m_1 \oplus m_2$ by accumulating basic beliefs of all the subsets of a hypothesis as demonstrated.

$$\begin{pmatrix} Bel_1 \oplus Bel_2(A,B) = m_1 \oplus m_2(A,B) + m_1 \oplus m_2(A) + m_1 \oplus m_2(B) \\ Bel_1 \oplus Bel_2(B,C) = m_1 \oplus m_2(B,C) + m_1 \oplus m_2(B) + m_1 \oplus m_2(C) \\ Bel_1 \oplus Bel_2(A) = m_1 \oplus m_2(A) \end{pmatrix} \quad (2)$$

For computational purposes, an "intersection table" with values of m_1 and m_2 along the rows and columns, respectively, is a helpful device. Table 1 shows the intersection table for m_1 and m_2 for the above example.

Table 1: Intersection table for two basic beliefs

		m_2	
		(B, C) (0.7)	Θ (0.3)
m_1	(A, B) (0.6)	(B) (0.42)	(A, B) (0.18)
	Θ (0.4)	(B, C) (0.28)	Θ (0.12)

In this example, a subset appears only once in the table, and $m_1 \oplus m_2$ is easily computed for the hypotheses on failure type:

$m_1 \oplus m_2(B)$=0.42
$m_1 \oplus m_2(A, B)$=0.18
$m_1 \oplus m_2(B, C)$=0.28
$m_1 \oplus m_2(\Theta)$=0.12
$m_1 \oplus m_2$ is 0 for all other subsets of Θ.

Then the selected combined belief functions have the following values:

$Bel_1 \oplus Bel_2(A, B)$=0.18+0.0+0.42=0.60
$Bel_1 \oplus Bel_2(B, C)$=0.28+0.42=0.70
$Bel_1 \oplus Bel_2(A)$=0.0.

3 Synergistic Diagnosis Model

3.1 Belief Combination

Belief combination for a diagnosis with multiple methods must satisfy several requirements. First, mutual exclusivity of singletons in a frame of discernment must be satisfied by the sets of hypotheses in the diagnosis method constituting the frames of discernment. In other words, the failure type A should be mutually exclusive of failure type B or C. Second, the belief functions that represent the evidence in the diagnosis method should have a particularly simple form. Third, the way the methods indicate failure type should fit well into the evidence theory. Since the diagnosis methods of plant facilities produce mutually exclusive failure types along with support/rejection degree or probability, the synergistic diagnosis for turbine generator plants is well suited for modeling with the Dempster-Shafer theory.

The basic reasoning element in the synergistic diagnosis model is a pair of the form of $\{\alpha, b_\alpha\}$ or $\{\sim\alpha, b_{\sim\alpha}\}$, where α indicates a failure type (A, B, or C for example) and b a numerical value. This pair gives rise to a single hypothesis of "a diagnosis method supports a failure type α with degree b_α" or "a diagnosis method rejects a failure type α with degree $b_{\sim\alpha}$." A frame of discernment (Θ) would then consist of all possible pairs for all α of a particular method.

If a method supports a failure type, for example $\alpha = A$, with degree b_A, then the basic belief b_A is assigned to the hypothesis A and $(1 - b_A)$ is assigned to Θ. If a method rejects the failure type A with degree $b_{\sim A}$, then $b_{\sim A}$ is assigned to the hypothesis $\sim A$, "not failure type A," and $(1 - b_{\sim A})$ is assigned to Θ. Then, using the intersection table, the combined belief is obtained. This model of belief function combination is illustrated in Figure 1.

Generally, there are three types of belief combination and they are explained along with basic belief assignment from the supporting/rejecting degree.

- **Type 1**: Two diagnosis methods are both supporting or both rejecting the same failure type. For example, both methods support A, one to degree 0.4 and the other to degree 0.7. Then, the pairs are $\{\alpha_1, b_{\alpha 1}\} = \{A, 0.4\}$ and $\{\alpha_2, b_{\alpha 2}\}=\{A, 0.7\}$. The effect of triggering these two is represented by basic beliefs m_1 and m_2, where $m_1(A) = 0.4$, $m_1(\Theta) = 0.6$, and $m_2(A) = 0.7$, $m_2(\Theta) = 0.3$. The combined effect on the belief is obtained by $m_1 \oplus m_2$.
- **Type 2**: One method is supporting and the other rejecting the same singleton hypothesis. For example, method 1 supports A to degree 0.4, and method 3 rejects A to degree 0.8. The effect of triggering these two methods is represented by basic beliefs m_1 and m_3, where m_1 is defined as in the example in Type 1 and $m_3(\sim A) = 0.8$ with $m_3(\Theta) = 0.2$. The combined effect on belief is obtained by $m_1 \oplus m_3$.
- **Type 3**: Two methods involve different hypotheses in the same frame of discernment. For example, method 1 supports failure type A to degree 0.4, and method 4 rejects failure type A to degree 0.7. The triggering of method 4 gives rise to m_4 defined by $m_4(\sim A) = 0.7$ with $m_4(\Theta) = 0.3$. The combined effect on belief is obtained by $m_1 \oplus m_4$.

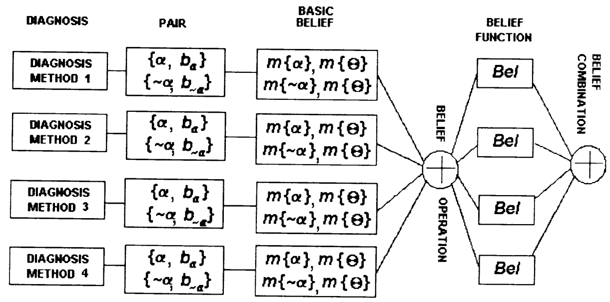

Figure 1: Belief combination scheme

The drawback of the above scheme is that the actual implementation of belief function combination, from basic beliefs using the Dempster-Shafer's evidence theory, involves complex mathematical calculations [11]. Therefore, we adopted a simplified approach which minimizes computational complexity by drawing the supporting and rejecting evidence directly from basic beliefs; this scheme eliminates the intermediate process of belief function calculation. Drawing evidence and combining evidence in a simplifying order to reduce computations is explained in [1].

3.2 Evidence Combination

The simplified scheme of evidence combination has two distinctive features:

- Derivation of $m\{\Theta\}$: Instead of deriving $m\{\Theta\}$ from $m\{\alpha\}$ and $m\{\sim\alpha\}$ from each method as in Figure 1, this simplified technique first combines all $m\{\alpha\}$ and $m\{\sim\alpha\}$ from all methods then derives $m\{\Theta\}$. Thus, we derive $m\{\Theta\}$ only once instead of as many times as the number of methods involved.

- "Evidence" instead of "belief function": We directly reach the combined evidence using $m\{\alpha\}$ or $m\{\sim\alpha\}$ instead of drawing belief functions by the intersection table of $m(\alpha)$ and $m(\sim\alpha)$ and combining the belief functions.

Based on the evidence combination technique, the synergistic diagnosis model has the structure of Figure 2. The steps for a simplified evidence combination model are explained below.

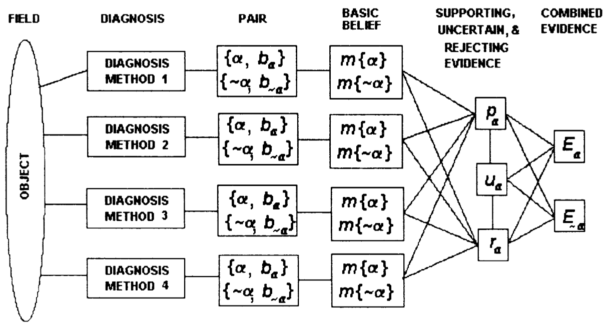

Figure 2: Synergistic diagnosis model with simplified evidence combination

- **Step 1**: For each singleton hypothesis α from all the methods, find the *combined supporting evidence* (p_α) by combining the basic beliefs that support a hypothesis. The combined supporting evidence for a hypothesis, say $\alpha = A$, for all the involved methods, $i = 1, ...N$, is defined by

$$p_A = \frac{\left\{1-\prod[1-m_i\{A\}]\right\}\cdot\left\{\prod[1-m_i\{\sim A\}]\right\}}{1-\left\{1-\prod[1-m_i\{A\}]\right\}\cdot\left\{1-\prod[1-m_i\{\sim A\}]\right\}} \tag{3}$$

Then, similarly, we obtain the *combined rejecting evidence* (r_α) for the hypothesis of failure type A for all the involved methods defined by

$$r_A = \frac{\left\{1-\prod[1-m_i\{\sim A\}]\right\}\cdot\left\{\prod[1-m_i\{A\}]\right\}}{1-\left\{1-\prod[1-m_i\{A\}]\right\}\cdot\left\{1-\prod[1-m_i\{\sim A\}]\right\}} \tag{4}$$

Since, for each failure type, the total evidence should become 1.0, the combined evidence for $\{\Theta\}$, defined as the *combined uncertain evidence* (u_α), is obtained by

$$u_A = 1.0 - p_A - r_A \tag{5}$$

- **Step 2**: We repeat the above step for all the hypotheses to obtain p_B, r_B, u_B, and so on.
- **Step 3**: The *combined evidence for a hypothesis* (E_α), say A, is defined by

$$E_A = K\left\{p_A\prod_{\alpha\neq A}(r_\alpha+u_\alpha)+u_A\prod_{\alpha\neq A}r_\alpha\right\} \tag{6}$$

and the *combined evidence against a hypothesis* ($E_{\sim\alpha}$), say A, is defined by

$$E_{\sim A} = K\cdot\left\{p_A\prod_{all}(r_\alpha+u_\alpha)\right\}\cdot\left\{\sum_{\alpha\neq A}\frac{p_\alpha}{(r_\alpha+u_\alpha)}\right\}$$

$$+K\cdot\left\{r_A\prod_{\alpha\neq A}(r_\alpha+u_\alpha)\right\}-K\cdot\left\{\prod_{all}r_\alpha\right\} \tag{7}$$

where

$$K = \frac{1}{\left\{\prod_{all}(r_\alpha+u_\alpha)\right\}\cdot\left\{1+\sum_{all}\frac{p_\alpha}{(r_\alpha+u_\alpha)}\right\}-\left\{\prod_{all}r_\alpha\right\}}$$

as long as $p_\alpha \neq 1$ for all α.

The combined evidence obtained from the last step determines the final decision on the hypothesis of failure types.

4 Synergistic Diagnosis of a Plant

Power plant equipment (such as boilers, pulverizers, feed pumps and fans, turbines, generators, etc.) is complex in nature and combined to make a complex system as well. Quick diagnosis of the system that leads to preventive maintenance has practical value for efficient plant operation. Total shutdown of the plant may be due to failures of boiler control, turbine bearing, or generator seal, however, partial shutdowns may be caused by other components such as draft fans and turbine blades. Therefore, in a turbine generator plant, boiler controls, generator seals, and turbine bearings must operate satisfactorily. This section presents an application of the synergistic diagnosis model to a turbine-generator power plant.

There are three areas of diagnosis for power plant facilities: diagnosis for electrical parts such as a generator winding and coil; diagnosis for mechanical parts such as unbalance, misalignment, oil whirl and looseness in bearings, shafts, or rotating units; and diagnosis for attached parts of refrigeration and circulation device units [10]. First, we will briefly review some of the important diagnosis methods.

- **Vibration Diagnosis Method**: Failure data reveal that between 30 percent and 50 percent of all fossil-fuel power plant downtime is caused by failure of rotating equipment; fans, pumps, drive turbines, and turbine-generators [5]. Generally, rotational machines have failure phenomena of misalignment, unbalance, rubbing, and oil whirl, and it is possible to diagnose rotational machine faults by examining the following parameters: main frequency range of failure signal, shape of rotational axle, and main vibration frequency range and magnitude on abnormal operation.

- **Insulation Diagnosis Method**: There are three methods in this area of diagnosis: Megger method, high voltage method, and partial discharge method. Megger diagnosis uses a Megger device to measure insulation resistance. The method identifies the insulation resistance necessary to operate rotational machines on normal operation. However, it is very difficult to determine a normal range for insulation in rotational machines such as generators and ancillary motors. DC high voltage diagnosis measures current level while applying DC high voltage to insulated material; current level is decreased with time if insulation level is low. Partial discharge occurs if insulating material has voids. When there is a void, applied voltage is decreased by the partial discharge of the void [4].
- **Acoustic Emission Method**: Acoustic emission diagnosis detects sudden energy release from cracks, variation and transformations of material. This method is used mainly to diagnose bearing damage caused by metallic rubbing, touching, internal particle occurrence, and invasion of foreign material [10].

4.1 Problems and Uncertainty in Plant Diagnosis

Although the vibration method is a fairly effective means of detecting failure, it can often misdiagnose equipment failure. Other methods also have their drawbacks. In insulation diagnosis, for example, since there are different void sizes in insulation material, partial discharges alone cannot effectively check the status of insulation failure [10].

Moreover, there are several diagnosis methods for each of the three areas. On the same unit of the power plant, diagnosis methods use the same or similar parameters as their inputs to determine the status of a unit. In some cases, a certain method supports failure type A in an element and another rejects failure type A, and another failure type B as illustrated in Figure 3.

Hence, it is extremely useful if we can find a way to combine the results of each individual diagnosis method to produce a resultant conclusion on the status and failure type of the unit in question. Actually, there is a trend in the U.S. where electric companies are moving toward the application of a combination of several independent diagnosis methods for effective predictive maintenance [4].

4.2 Application of the Synergistic Diagnosis Model

Assume that there are three different failure types to be identified in a power plant: "crack of turbine shaft" (SHAFT), "blade damage" (BLADE), and "bearing damage" (BEARING). As an example of practical application of the synergistic diagnosis model, consider the net effect of the following set of eight different methods for turbine generator diagnosis in Table 3.

To find the combined evidence on each of the failure types, we follow the steps introduced for the synergistic diagnosis.

Step 1: Basic Belief. Based on the information given above of the entities, we have the basic beliefs for all the methods as indicated in Table 4.

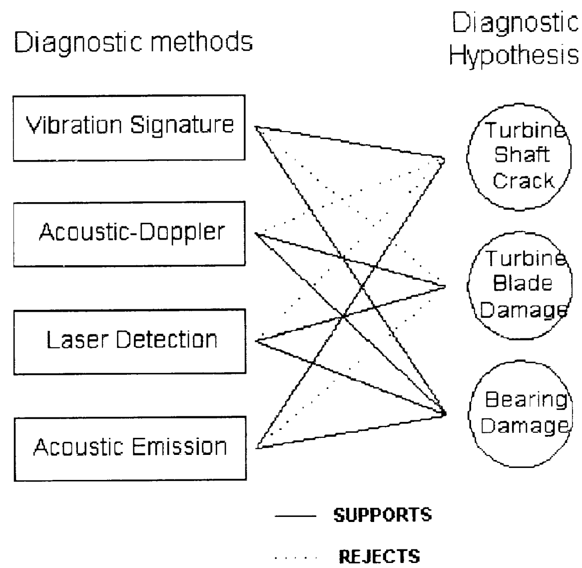

Figure 3: A hypothetical situation in plant diagnosis

Table 3: Entities from Eight Fictitious Diagnosis Methods

Method No.	Failure type	Supporting/rejecting	Degree
1	SHAFT	Rejecting	0.6
2	SHAFT	Rejecting	0.2
3	BEARING	Supporting	0.4
4	BLADE	Rejecting	0.8
5	BEARING	Supporting	0.3
6	SHAFT	Rejecting	0.5
7	SHAFT	Supporting	0.3
8	BLADE	Supporting	0.7

Table 4: Basic Beliefs of the Diagnosis Methods

Hypothesis	Basic Beliefs
SHAFT	$m_1\{\sim\text{SHAFT}\}=0.6$ $m_2\{\sim\text{SHAFT}\}=0.2$ $m_6\{\sim\text{SHAFT}\}=0.5$ $m_7\{\text{SHAFT}\}=0.3$
BEARING	$m_3\{\text{BEARING}\}=0.4$ $m_5\{\text{BEARING}\}=0.3$
BLADE	$m_4\{\sim\text{BLADE}\}=0.8$ $m_8\{\text{BLADE}\}=0.7$

Step 2: Calculation of evidence: p_α, r_α, and u_α. Next, we calculate the evidence for each of the hypotheses. For "SHAFT," using the evidence equations, we obtain the following evidences:

$$p_{SHAFT} = \frac{\left\{1-\prod[1-m_i\{SHAFT\}]\right\}\cdot\left\{\prod[1-m_i\{\sim SHAFT\}]\right\}}{1-\left\{1-\prod[1-m_i\{SHAFT\}]\right\}\cdot\left\{1-\prod[1-m_i\{\sim SHAFT\}]\right\}}$$

$$= \frac{\{1-[1-0.3]\}\{[1-0.6][1-0.2][1-0.5]\}}{1-\{1-[1-0.3]\}\{1-[1-0.6][1-0.2][1-0.5]\}} = \frac{0.048}{0.748} = 0.064$$

$$r_{SHAFT} = \frac{\left\{1-\prod m_i\{\sim SHAFT\}\right\}\cdot\left\{\prod m_i\{SHAFT\}\right\}}{1-\left\{1-\prod m_i\{SHAFT\}\right\}\cdot\left\{1-\prod m_i\{\sim SHAFT\}\right\}}$$

$$= \frac{\{1-[1-0.6][1-0.2][1-0.5]\}\{1-0.3\}}{0.748} = \frac{0.588}{0.748} = 0.786$$

$$u_{SHAFT} = 1.0 - p_{SHAFT} - r_{SHAFT} = 1.0 - 0.064 - 0.786 = 0.15$$

By the same procedure, for "BLADE" and "BEARING," we get the following supporting, rejecting, and uncertain evidence:

$p_{BLADE} = 0.318$, $r_{BLADE} = 0.545$, and $u_{BLADE} = 0.137$

$p_{BEARING} = 0.58$, $r_{BEARING} = 0.0$, and $u_{BEARING} = 0.42$

Step 3: Evidence Combination. For an easier combination and application of the model, we generate a table for the parameters for calculation of K and E as shown below. In the table, we add a column for "$r + u$" for easy substitution in the equations.

	p	r	u	$r+u$
SHAFT	0.064	0.786	0.150	0.936
BLADE	0.318	0.545	0.137	0.682
BEARING	0.580	0.000	0.420	0.420

Assessing the effects of evidence in the various failure types, we first calculate the index K:

$$K = \frac{1}{\left\{\prod_{all}(r_\alpha + u_\alpha)\right\}\cdot\left\{1+\sum_{all}\frac{p_\alpha}{(r_\alpha+u_\alpha)}\right\} - \left\{\prod_{all} r_\alpha\right\}}$$

$$= \frac{1}{(0.936)(0.682)(0.42)\left\{1+\frac{0.064}{0.936}+\frac{0.318}{0.682}+\frac{0.58}{0.42}\right\} - (0.786)(0.545)(0.)} = 1.28$$

Then the combined evidence of "SHAFT" can be found as shown below:

$$E_{SHAFT} = K\left\{p_{SHAFT}\prod_{\alpha\neq SHAFT}(r_\alpha + u_\alpha) + u_{SHAFT}\prod_{\alpha\neq A} r_\alpha\right\}$$

$$= 1.28\cdot[(0.064)(-.682)(0.42) + (0.15)(0.545)(0.0)]$$

$$= 1.28\cdot 0.018 = 0.023$$

Similarly, we find the other two pieces of the combined evidence as follows:

$E_{BLADE} = 0.160$, and $E_{BEARING} = 0.704$

From the above result, we conclude that the failure type of the turbine generator is most likely a "BEARING" problem with a very slight chance of "BLADE" problem. The possibility of "SHAFT" problem is extremely small.

As seen from the example, synergistic diagnosis using Dempster-Shafer theory is particularly appealing for failure diagnosis. Figure 4 shows a possible implementation of the suggested synergistic diagnosis model for an actual turbine generator using a data acquisition system, a communication module for remote access, and a monitoring workstation in which the diagnosis methods and the synergistic model algorithms reside.

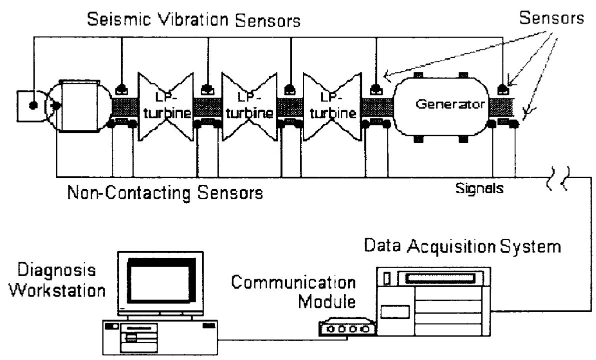

Figure 4: Practical application example of synergistic diagnosis for turbine generator

5 Conclusions

To secure reliable plant operation, it is necessary to provide a predictive maintenance system for plant facilities. Even though there are several failure diagnosis methods available, they are imprecise and their information on failure type identification is incomplete and uncertain. This paper provides a formal framework to implement a combined set of diagnosis methods into synergistic diagnosis by applying uncertainty reasoning. We utilize the evidence theory of Dempster-Shafer on uncertainty and belief combination to combine several different diagnosis methods and their uncertain diagnostic results. We present a practical application example for plant diagnosis with detailed calculation and explanation. In addition, we suggest a practical design for an actual turbine generator plant using the proposed synergistic model.

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