

Fault Diagnosis of Turbine Using an Improved Intuitionistic Fuzzy Cross Entropy Approach

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Abstract—The fuzzy cross entropy of intuitionistic fuzzy sets, so-called intuitionistic cross entropy, is introduced by analogy with the cross entropy of probability distributions. This paper introduces the concepts of discrimination information and cross-entropy in the intuitionistic fuzzy sets. Based on this improved entropy measure, we add information of an intuitionistic fuzzy index and reveal an intuitive and mathematical connection between the notions of entropy for intuitionistic fuzzy sets in terms of fuzziness and intuitionism. Finally, a fault diagnosis example of the turbine has been illustrated. The example demonstrates that the proposed method cannot only diagnose the main fault types of the turbine, it can also detect useful information for future trends and multi-fault analysis.

Keywords—Intuitionistic fuzzy sets; cross-entropy; similarity measure; fault diagnosis

I. INTRODUCTION

The technique of fault diagnosis has produced the huge economic benefits by scheduling preventive maintenance and preventing extensive downtime periods caused by extensive failure. Therefore, it has become a research hotspot. However, fault occurred in a very complex mechanism, the same set of signs of failure which were observed, may be caused by the other failure reasons, in addition, the Characteristics of state failure which were extracted from the failure detection often have a characteristics of fuzziness, coupled with the uncertainty of the signs and the very failures, such as the fuzziness of the sign, the uncertainty of the knowledge of empirical diagnosis and so on, making the problems of diagnosis even more difficult. Fuzzy relative theory can be a good description and characterization of this complex concept, and use the method of computing and transform the vague sets for fault diagnosis and reasoning.

The steam turbine generator unit is a kind of important equipments in power plant with complexity in equipment structure and particularity in operating environment. Failures of steam turbine generator units can usually be specified according to the different amplitude ratio of vibration signal in several different frequency ranges [16]. Since the failure and its vibration symptom are not one-to-one corresponding, many

studies have been performed on the intelligent diagnosis methods for turbine generator based on expert system (such as [22], [23], [13], [7], [24]), artificial neural network (such as [17], [6], [9], [28], [11]) fuzzy theory or their combination in recent years (such as [10], [8], [25], [26]).

In the problem at hand, little research has been devoted to the situation where the value of the amplitude ratio of vibration signal is vague and linguistic ambiguity. Actually the value of the amplitude ratio of vibration signal in real circumstance is usually inaccuracy and vague valued. The estimation of precise value of possibility becomes very difficult in many cases. So the methods mentioned above would thus obtain wrong results under the intuitionistic fuzzy circumstance for they could not get the precise value of amplitude ratio of vibration signal.

The aim of this paper is to develop a fault diagnosis method of turbine based on an improved cross entropy measures under the intuitionistic fuzzy circumstance. In order to handle the uncertain situation and insufficient vague information, a concept of intuitionistic fuzzy sets (IFSs) developed by Atanassov [1] is introduced in this paper. The fundamental characteristics of IFSs are that the values of its membership function and non-membership vague values rather than exact numbers. Therefore, it could be used to simulate any activities and process requiring human expertise and knowledge, which are inevitably imprecise values. The distance between two IFSs is also defined taking into account the intuitionistic fuzzy values. And the similarity measure is conducted based on the Euclidean distance. Then, a new method of the fault diagnosis of turbine is presented in the basis of the cross entropy measures among IFSs. The similarity degree between the detecting sample and the knowledge of system fault is evaluated in the fault diagnosis of turbine vibration by the proposed measured method among IFSs. The smaller the value of distance measure, the more the similarity between the detecting sample and a type of fault knowledge. Then, the type of vibration fault is determined according to the value of similarity measure. Examples explain the validity and reasonability in the fault diagnosis problems based on the distance measures among IFSs.

The remainder of this study is organized as follows: In Section II, the relative basic concepts including IFSs, fuzzy cross-entropy (FCE) and intuitionistic fuzzy cross-entropy (IFCE) method are described. Section III presents an improved

IFCE approach, and illustrates an example for fault diagnosis in Section IV. Finally, a conclusion is drawn in section V.

II. RELATED WORKS

A. IFSs Theory

Fuzzy sets theory has proposed by Zadeh in 1965 [27], has shown successful applications in various fields. A fuzzy set is defined as: $\tilde{A} = \{(x, \mu_{\tilde{A}}(x)) | x \in U, \mu_{\tilde{A}}(x) \in [0, 1]\}$, where $U \ni x$ is the universe of discourse and $\mu_{\tilde{A}}(x) \in [0, 1]$ is the membership function of A . For further details, the reader may refer to [27].

In this theory, the membership of an element to a fuzzy set is a single value between zero and one. But in reality, it may not always be certain that the degree of non-membership of an element to a fuzzy set is just equal to 1 minus the degree of membership, i.e. there may be some intuitionistic fuzzy index. Thus, as a generalization of fuzzy sets, the concept of IFSs was introduced by Atanassov in 1986. Bustince and Burillo [5] showed that this notion coincides with the notion of vague sets (VSs).

The IFSs is as an extension of fuzzy sets. An IFSs A in a fixed set E is an objective with the expression

$$A = \{(x, \mu_A(x), \nu_A(x)) | x \in E\}, \quad (1)$$

where the functions $\mu_A : E \rightarrow [0, 1]$ and $\nu_A : E \rightarrow [0, 1]$ denote the degree of membership and the degree of non-membership of the element $x \in E$, respectively. For every $x \in E$,

$$0 \leq \mu_A(x) + \nu_A(x) \leq 1. \quad (2)$$

When $\mu_A(x) + \nu_A(x) = 1$, for every $x \in E$, then the IFSs will degenerate to a fuzzy set. Hence, we can consider a fuzzy set with its membership function $u_A(x)$, having the IFSs expression as

$$A = \{(x, \mu_A(x), 1 - \mu_A(x)) | x \in E\}. \quad (3)$$

Under the condition of $\nu_A(x) = 1 - \mu_A(x)$, for every $x \in E$.

For each IFSs A in E , "intuitionistic fuzzy index" has consideration. We call the intuitionistic fuzzy index of an element $x \in E$ in A by the following expression:

$$\pi_A(x) = 1 - \mu_A(x) - \nu_A(x), \quad (4)$$

we can consider $\pi_A(x)$ as an intuitionistic fuzzy index of x to A . From Eq.(4) it is evident that

$$0 \leq \pi_A(x) \leq 1 \text{ for all } x \in E. \quad (5)$$

Therefore, to describe an intuitionistic fuzzy set completely; we need at least two functions from the triplet ([2][3]): (1) membership function; (2) non-membership function; (3) intuitionistic fuzzy index.

B. FCE Method

Let us recall the definition of the cross entropy by Shannon in 1948 [19]. Let $P = \{p(x_i), i = 1, 2, \dots, n\}$ is a probability

distribution on X . where $p(x_i) \in [0, 1]$ and $\sum_{i=1}^n p(x_i) = 1$. Then

the entropy of probability distribution P has been defined as follows,

$$H(P) = - \sum_{x_i \in X} p(x_i) \ln p(x_i). \quad (6)$$

Kullback [12] advance lets $Q = \{q(x_i), i = 1, 2, \dots, n\}$ as the other probability distributions of the discrete random variable X , where $q(x_i) \in [0, 1]$ and $\sum_{i=1}^n q(x_i) = 1$. Then the cross-entropy measure of P from Q can be obtained as

$$H(P, Q) = \sum_{x_i \in X} p(x_i) \ln \frac{p(x_i)}{q(x_i)}, \quad (7)$$

which measures the amount of discrimination of P from Q . However, Lin [15] pointed out that Eq. (7) is undefined if $q(x_i) = 0$ and $p(x_i) = 0$ for any $x_i \in X$. In order to overcome this drawback, a modified cross-entropy measure has be provided as

$$H(P, Q) = \sum_{x_i \in X} p(x_i) \ln \frac{p(x_i)}{\frac{1}{2} p(x_i) + \frac{1}{2} q(x_i)}. \quad (8)$$

Based on Eq. (8), Shang and Jiang [18] defined the FCE approach between two fuzzy numbers as the following,

$$M_{FS}(\tilde{A}, \tilde{B}) = \sum \left(\mu_A(x_i) \ln \frac{\mu_A(x_i)}{\frac{1}{2}(\mu_A(x_i) + \mu_B(x_i))} + (1 - \mu_A(x_i)) \ln \frac{1 - \mu_A(x_i)}{1 - \frac{1}{2}(\mu_A(x_i) + \mu_B(x_i))} \right). \quad (9)$$

Due $M_{FS}(\tilde{A}, \tilde{B})$ is not symmetric with respect to its arguments. Thus, Shang and Jiang [18] have also defined a symmetric discrimination information measure as the following,

$$D_{FS}(\tilde{A}, \tilde{B}) = M_{FS}(\tilde{A}, \tilde{B}) + M_{FS}(\tilde{B}, \tilde{A}). \quad (10)$$

In addition, Shang and Jiang [18] have proofed that $D_{FS}(\tilde{A}, \tilde{B}) \geq 0$ and $D_{FS}(\tilde{A}, \tilde{B}) = 0$ if and only if $\tilde{A} = \tilde{B}$.

Based on above mentions theoretical background, an intuitionistic fuzzy cross entropy method has been described as the next subsection.

C. IFCE Method

Let us consider two sets $A, B \in U(X)$. In order to derive a cross-entropy measure for IFSs, we have to exploit the information carried by both the membership and the non-membership function. In an analogous manner to Bhandari and Pal [4], we consider the following quantity:

$$H^\mu(A, B; x_i) = \ln \frac{\mu_A(x_i)}{\mu_B(x_i)}, \quad (11)$$

as the amount of information for discrimination of $u_A(x_i)$ from $u_B(x_i)$. Therefore, the expected information for discrimination of A against B , based solely on the membership function, is given by

$$H^\mu(A, B) = \sum_{i=1}^n \mu_A(x_i) \ln \frac{\mu_A(x_i)}{\mu_B(x_i)}. \quad (12)$$

Similarly, considering the non-membership function we have

$$H^v(A, B) = \sum_{i=1}^n v_A(x_i) \ln \frac{v_A(x_i)}{v_B(x_i)}. \quad (13)$$

Hence, the information for discrimination in favor of A against B is obtained as the sum of the quantities $H^u(A, B)$ and $H^v(A, B)$, i.e.,

$$H''_{IFS}(A, B) = \sum_{i=1}^n \left[\mu_A(x_i) \ln \frac{\mu_A(x_i)}{\mu_B(x_i)} + v_A(x_i) \ln \frac{v_A(x_i)}{v_B(x_i)} \right]. \quad (14)$$

In order to overcome the drawback of Eq. (14) being undefined if $u_B(x_i) = 0$ or $v_B(x_i) = 0$ for any $x_i \in X$, a modified version of Eq. (14) is introduced based on Eq. (8) and is given by

$$H_{IFS}(A, B) = \sum_{i=1}^n \left[\mu_A(x_i) \ln \frac{\mu_A(x_i)}{\frac{1}{2}(\mu_A(x_i) + \mu_B(x_i))} + v_A(x_i) \ln \frac{v_A(x_i)}{\frac{1}{2}(v_A(x_i) + v_B(x_i))} \right] \quad (15)$$

According to Shannon's inequality, Lin [15] pointed out that one can easily prove that $H_{IFS}(A, B) \geq 0$ and $H_{IFS}(A, B) = 0$ if and only if $A = B$. A similar measure for FSs, denoted by $H_{FS}(\tilde{A}, \tilde{B})$, was defined by Bhandari and Pal [4]. For FSs in general $H_{FS}(\tilde{A}, \tilde{B}) \neq H_{FS}(\tilde{A}^c, \tilde{B}^c)$. However, for IFSs the following equality holds:

$$H_{IFS}(A, B) = H_{IFS}(A^c, B^c), \quad (16)$$

where A^c and B^c are the complementary sets of A and B , respectively. Therefore, in analogy with Eq. (9), we proceed to the following definition of the intuitionistic fuzzy cross-entropy.

Definition 1. For two sets $A, B \in U(X)$, $H_{IFS}(A, B)$ is the intuitionistic fuzzy cross-entropy between A and B . $H_{IFS}(A, B)$ can also be called discrimination information for IFSs. However, one can observe that $H_{IFS}(A, B)$ is not symmetric with respect to its arguments. Therefore, a symmetric measure is defined as follows:

Definition 2. For two sets $A, B \in U(X)$,

$$D_{IFS}(A, B) = H_{IFS}(A, B) + H_{IFS}(B, A) \quad (17)$$

is called a symmetric discrimination information measure for IFSs. It can easily be verified that $H_{IFS}(A, B)$ and $D_{IFS}(A, B)$ degenerate to their fuzzy counterparts when A and B are FSs.

III. AN IMPROVED IFCE APPROACH

It is easy to see that cross-entropy proposed by Vlachos and Sergiadis [21] only involve the first two parameters. That is, the membership degree and non-membership degree of IFSs. Furthermore, it does not take the third parameter (intuitionistic fuzzy index) into account in the above derivation and discrimination measure of IFSs.

Furthermore, Szmidt and Kacprzyk [20] have showed that omitting one of the three parameters may lead to incorrect results, and thus all the three parameters should be taken into

account when calculating association or distance between two IFSs.

Motivated by the idea of Szmidt and Kacprzyk [20], we improve the feasibility of original IFCE by add the third parameter (intuitionistic fuzzy index) consideration. Therefore, a modified formulation is improved to reach better discrimination measure of IFCE approach.

Following the Eqs. (12) and (13), we may keep considering the function of an intuitionistic fuzzy index for discrimination measure similarly. Thus, we can obtained

$$H^\pi(A, B) = \sum_{i=1}^n \pi_A(x_i) \ln \frac{\pi_A(x_i)}{\pi_B(x_i)}. \quad (18)$$

Next, the information for discrimination in favor of A against B can be calculated as the sum of the quantities $H^u(A, B)$, $H^v(A, B)$, and $H^\pi(A, B)$. The Eq. (14) can be revised as

$$H'_{IFS}(A, B) = \sum_{i=1}^n \left[\mu_A(x_i) \ln \frac{\mu_A(x_i)}{\mu_B(x_i)} + v_A(x_i) \ln \frac{v_A(x_i)}{v_B(x_i)} + \pi_A(x_i) \ln \frac{\pi_A(x_i)}{\pi_B(x_i)} \right]. \quad (19)$$

To avoid the drawback of Eq. (19) being undefined if $u_B(x_i) = 0$, $v_B(x_i) = 0$ or $\pi_B(x_i) = 0$ for any $x_i \in X$, an improved version of Eq. (19) is introduced based on Eq. (15) and is given as

$$H_{IFS}(A, B) = \sum_{i=1}^n \left[\mu_A(x_i) \ln \frac{\mu_A(x_i)}{\frac{1}{2}(\mu_A(x_i) + \mu_B(x_i))} + v_A(x_i) \ln \frac{v_A(x_i)}{\frac{1}{2}(v_A(x_i) + v_B(x_i))} + \pi_A(x_i) \ln \frac{\pi_A(x_i)}{\frac{1}{2}(\pi_A(x_i) + \pi_B(x_i))} \right] \quad (20)$$

One can also prove that $H_{IFS}(A, B) \geq 0$ and $H_{IFS}(A, B) = 0$ if and only if $A = B$, according to Shannon's inequality. A similar measure for IFSs, the following equality also holds:

$$H_{IFS}(A, B) = H_{IFS}(A^c, B^c), \quad (21)$$

where A^c and B^c are the complementary sets of A and B , respectively. Therefore, in analogy with Eq. (20), we can also proceed to the symmetric discrimination definition of the proposed intuitionistic fuzzy cross-entropy.

$$D_{IFS}(A, B) = H_{IFS}(A, B) + H_{IFS}(B, A) \quad (22)$$

IV. ILLUSTRATIVE EXAMPLE FOR FAULT DIAGNOSIS OF TURBINE

In this section, the proposed measured method is applied to fault diagnosis of steam turbine generator unit under intuitionistic fuzzy circumstance. The knowledge of system fault and detecting sample adopted from Li and Wan [14] are listed. We select the amplitude ratio of vibration signal in six different frequency ranges, such as less than $0.4f$, $0.5f$, f , $2f$, $3f$ and more than $3f$, as the characteristic value. Therein, f is the fundamental frequency of the rotor. Three typical failures are selected as failures pattern. Here, P_1 is oil whip, P_2 is unbalance, P_3 is misalignment. And B_1 , B_2 are the two samples to be evaluated.

Table I presents the six different frequency ranges for the failures pattern. Another, the six different frequency ranges for two samples are evaluated in Table II. Each element of the tables, is given in the form of a pair of numbers corresponding to the membership, non-membership values, respectively, e.g., the pattern (P_1) vs. frequency ($< 0.4f$) is described by $(\mu, \nu) = (0.06, 0.84)$.

TABLE I. THE KNOWLEDGE OF SYSTEM FAULT PATTERN

	$< 0.4f$	$0.5f$	f	$2f$	$3f$	$> 3f$
P_1	(0.06, 0.84)	(0.84, 0.02)	(0.20, 0.75)	(0.02, 0.89)	(0.20, 0.75)	(0.01, 0.92)
P_2	(0.01, 0.93)	(0.02, 0.90)	(0.90, 0.01)	(0.08, 0.85)	(0.01, 0.89)	(0.02, 0.93)
P_3	(0.01, 0.94)	(0.01, 0.94)	(0.40, 0.42)	(0.40, 0.44)	(0.28, 0.56)	(0.10, 0.61)

TABLE II. THE CHARACTERISTIC FOR THE SAMPLES CONSIDERED

	$< 0.4f$	$0.5f$	f	$2f$	$3f$	$> 3f$
B_1	(0.01, 0.96)	(0.00, 0.97)	(0.37, 0.60)	(0.46, 0.51)	(0.31, 0.66)	(0.21, 0.75)
B_2	(0.00, 0.98)	(0.05, 0.92)	(0.69, 0.27)	(0.04, 0.93)	(0.03, 0.94)	(0.00, 0.97)

In order to find a proper diagnosis, we calculate for each sample, B_i , where $i \in \{1, 2\}$, the symmetric discrimination information measure for IFSs $D_{IFS}(P_j, B_i)$ between sample characteristics and the set of knowledge for system fault pattern that are characteristics for each fault diagnosis P_j , with $j \in \{1, 2, 3\}$. Based on Eq. (22), we assign the lowest symmetric discrimination information measure to the i th sample the diagnosis. Therefore, we assign to the i th sample the diagnosis whose characteristics have the lowest symmetric discrimination information measure from sample's characteristics. The fault diagnosed results for the considered samples are given in Table III.

According to Table III, we know that the degree of distance between failure pattern P_j , $j = 1, 2, 3$, and sample B_1 has been ranked and we have $D_{IFS}(P_3, B_1) > D_{IFS}(P_2, B_1) > D_{IFS}(P_1, B_1)$. It is clear that the degree of distance between P_3 and B_1 is the smallest one, the sample B_1 belongs to fault P_3 and the most possible type of vibration fault is misalignment. Also we have $D_{IFS}(P_2, B_2) > D_{IFS}(P_3, B_2) > D_{IFS}(P_1, B_2)$. from Table III and the degree of distance between P_2 and B_2 is the smallest one, the sample B_2 belongs to fault P_2 and the most possible type of vibration fault is unbalance.

TABLE III. THE DIAGNOSED RESULTS BY THE IMPROVED IFCE APPROACH

	Information measure		
	$D_{IFS}(P_1, B_i)$	$D_{IFS}(P_2, B_i)$	$D_{IFS}(P_3, B_i)$
Sample 1	2.5233	1.5131	0.4754
Rank	3	2	1
	Information measure		
	$D_{IFS}(P_1, B_i)$	$D_{IFS}(P_2, B_i)$	$D_{IFS}(P_3, B_i)$
Sample 2	2.1259	0.3906	1.2854
Rank	3	1	2

V. CONCLUSIONS

In this paper, taking into account the intuitionistic fuzzy sets, an improved cross entropy measure of IFSs on the basis of the Euclidean distance was defined. And the proposed method has been applied to the fault diagnosis of turbine among IFSs in this paper. This method can overcome the situation that the value of the amplitude ratio of vibration signal is uncertain and thus has promising future in the engineering application. Furthermore, ranking of the similarity degree can not only reveal the most possible type of fault occurred but also point out the sequence of fault diagnosis. Finally, an illustrative example has been provided to illustrate the validity and reasonability of the developed approach.

ACKNOWLEDGMENTS

This research is partially supported by the National Science Council of the Republic of China, Taiwan with Grant no. NSC 99-2410-H-606-005.

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