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Measure of Fuzziness with fuzzy entropy function

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Abstract

The relations of fuzzy entropy, distance measure, and similarity measure are discussed in this paper. For the purpose of reliable signal selection, the fuzzy entropy is proposed by a distance measure. Properness of the proposed entropy is verified by the definition of the entropy measure. Fourier and Wavelet transform are applied to the stator current signal to obtain the fault features of an induction motor. Membership functions for 3-phase currents are obtained by the Bootstrap method and Central Limit Theorem. Finally, the proposed entropy is applied to measure the fault signal of an induction machine, and the fuzzy entropy values of phase currents are illustrated.

Key Words : Fuzzy entropy, distance measure, fault signal.

I. Introduction

Characterization and quantification of fuzziness are important issues that affect the management of uncertainty in many system models and designs. The results that entropy of a fuzzy set is a measure of fuzziness of the fuzzy set are known by the previous researchers [1-7]. Liu had proposed the axiomatic definitions of entropy, distance measure and similarity measure, and discussed the relations between these three concepts. Kosko viewed the relation between distance measure and fuzzy entropy. Bhandari and Pal gave a fuzzy information measure for discrimination of a fuzzy set relative to some other fuzzy set. Pal and Pal analyzed the classical Shannon information entropy. Also Ghosh used this entropy to neural network. However, it is uncommon application of proposed entropy to the object in these studies. Hence we carried out the application of fuzzy entropy to the membership function of the faulted motor stator current.

In this paper, we proposed a fuzzy entropy with a distance measure. The proposed fuzzy entropy which has the simple structure compared to the previous proposed entropy is derived in Theorem 3.2 by the well-known Hamming distance measure. With the proposed entropy, we represent another similar entropy. We have proved that these proposed entropies satisfy the definition of entropy. Usefulness of two entropies are verified by the application of measure the fuzziness of the 3-phase faulted induction motor stator current. Generally, 4 classes of induction motor faults are known as bearing fault, rotor bar failure, eccentricity and stator winding problem [8-12]. In previous results, they have used arbitrary just one phase current. Hence we carried out the fuzzy entropy characterization to measure fuzziness of the membership function of each phase currents. For the decision of faulted motor, phase stator current is transformed via Wavelet decomposition [14], [15], and among the obtained coefficients the 4th coefficient of the 6th detail is used to decide which fault take places. From the 20 coefficients of the 4th coefficient of the 6th detail we process Bootstrap method [16], and we also obtain the membership function via Central Limit Theorem [16]. Using the proposed fuzzy entropy we measure the entropies of each phase current.

In the next section, the axiomatic definitions of entropy, distance measure and similarity measure of fuzzy sets are introduced and some basic relations between these measures are discussed. In Section 3, entropy is induced by the distance measure. In Section 4, fault signals are measured by the proposed entropy measure. Conclusions are followed in Section 5.

Notations: Through out this paper, $R^+=[0,\infty)$, $F(X)$, and $P(X)$ represent the set of all fuzzy sets and crisp sets on the universal set X respectively. $\mu_A(x)$ is the membership function of $A\in F(X)$, and the fuzzy set A, we use A^C to express the complement of A, i.e. $\mu_{A^c}(x)=1-\mu_A(x)$, $\forall x\in X$. For fuzzy sets A and B, $A\bigcup B$, the union of A and B is defined as $\mu_{A\cup B}(x)=\max(\mu_A(x),\mu_B(x))$, $A\bigcap B$, the intersection of A and B is defined as $\mu_{A\cap B}(x)=\min(\mu_A(x),\mu_B(x))$. A

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fuzzy set A^* is called a sharpening of A, if $\mu_{A^*}(x) \geq \mu_A(x)$ when $\mu_A(x) \geq 1/2$ and $\mu_{A^*}(x) \leq \mu_A(x)$ when $\mu_A(x) < 1/2$. For any crisp sets D, A_{near} and A_{far} of fuzzy set A are defined as

$$\mu_D(x) = \begin{cases} \frac{1}{2} & x \in D \\ 0 & x \notin D \end{cases}, \quad \mu_{A_{near}}(x) = \begin{cases} 1 & \mu_A(x) \geq \frac{1}{2} \\ 0 & \mu_A(x) < \frac{1}{2} \end{cases}$$

$$\mu_{A_{far}}(x) = \begin{cases} 0 & \mu_A(x) \geq \frac{1}{2} \\ 1 & \mu_A(x) < \frac{1}{2} \end{cases}.$$

II. Fuzzy entropy

In this section, we introduce some preliminary results and also discuss induced results. Liu suggested three axiomatic definitions of fuzzy entropy, distance measure and similarity measure as follows [4]. By these definitions, we can induce entropy, and compare it with the result of Liu.

Definition 2.1 (Liu, 1992) A real function e: $F(X) \to R^+$ or e: $P(X) \to R^+$ is called an entropy on $F(X)$, or $P(X)$ if e has the following properties:

(E1) $e(D) = 0$, $\forall D \in P(X)$

(E2) $e([1/2]) = \max_{A \in F(X)} e(A)$

(E3) $e(A^*) \leq e(A)$, for any sharpening A^* of A

(E4) $e(A) = e(A^c)$, $\forall A \in F(X)$.

where $[\frac{1}{2}]$ is the fuzzy set in which the value of the membership function is $1/2$.

Let $S(x)$ be $S(x) = -x\ln x - (1-x)\ln(1-x)$, $0 \leq x \leq 1$. For fuzzy set A one of entropies can be represented by

$$e(A) = -\sum_{i=1}^{n} (S(\mu_A(x_i)), \forall A \in F(X), \quad (1)$$

where $X = x_1, x_2, \cdots x_n$. Then (1) satisfies the properties of (E1) - (E4), and it can be easily proved.

Definition 2.2 [Liu, 1992] A real function d: $F^2 \to R^+$ is called a distance measure on $F(X)$, or $P(X)$ if d satisfies the following properties:

(D1) $d(A, B) = d(B, A)$, $\forall A, B \in F(X)$

(D2) $d(A, A) = 0$, $\forall A \in F(X)$

(D3) $d(D, D^c) = \max_{A, B \in F} d(A, B)$, $\forall D \in P(X)$

(D4) $\forall A, B, C \in F(X)$, if $A \subset B \subset C$, then $d(A, B) \leq d(A, C)$ and $d(B, C) \leq d(A, C)$.

Distance measure can have various formulations. One of distance measure between fuzzy sets A and B takes the following form

$$d(A, B) = \left(\frac{1}{n} \sum_{i=1}^{n} |\mu_A(x_i) - \mu_B(x_i)|^p\right)^{1/p}$$

for any integer $p \geq 1$. (2)

Futhermore, fuzzy normal distance measure is obtained by the multiplication of $1/\max_{C, D \in F} d(A, C)$.

Definition 2.3 (Liu, 1992) A real function s: $F^2 \to R^+$ or $P^2 \to R^+$ is called a similarity measure, if s has the following properties:

(S1) $s(A, B) = d(B, A)$, $\forall A, B \in F(X)$

(S2) $s(A, A^c) = 0$ $\forall A \in F(X)$

(S3) $s(D, D) = \max_{A, B \in F} s(A, B)$, $\forall A, B \in F(X)$

(S4) $\forall A, B, C \in F(X)$, if $A \subset B \subset C$, then $s(A, B) \geq s(A, C)$ and $s(B, C) \geq s(A, C)$.

Liu also pointed out that there is an one-to-one relation between all distance measures and all similarity measures, $d + s = 1$. Fuzzy normal similarity measure on F is also obtained by the division of $\max_{C, D \in F} s(C, D)$.

If We divide universal set X into two parts D and D^C in $P(X)$, then the fuzziness of fuzzy set A be the sum of the fuzziness of $A \cap D$ and $A \cap D^C$. By this idea, following definition is followed.

Definition 2.4. (Fan and Xie, 1999) Let e be an entropy on $F(X)$. Then for any $A \in F(X)$,

$$e(A) = e(A \cap D) + e(A \cap D^c)$$

is σ-entropy on $F(X)$.

Definition 2.5. (Fan and Xie, 1999) Let d be a distance measure on $F(X)$. Then for any $A, B \in F(X)$, and $D \in P(X)$,

$$d(A, B) = d(A \cap D, B \cap D) + d(A \cap D^c, B \cap D^c)$$

be the σ-distance measure on $F(X)$.

Definition 2.6. (Fan and Xie) Let s be a similarity measure on $F(X)$. Then for any $A, B \in F(X)$, and $D \in P(X)$,

$$s(A, B) = s(A \cap D, B \cup D^c) + s(A \cap D^c, B \cup D)$$

be the σ-similarity measure on $F(X)$.

From definition 2.4-6, we can focus interesting area of universal set and extend the theory of entropy, distance measure and similarity measure of fuzzy sets. Fan and Xie derived new entropy via defined entropy, which is introduces by $e' = e/(2 - e)$, where e is an entropy on $F(X)$. To discriminate between entropies, we give another entropy using Fan's idea.

Theorem 2.1 If e is an entropy on $F(X)$, then $\hat{e} = e^k$ is also an entropy on $F(X)$, where real number $k > 1$.

Proof. It is clear that $0 \leq \hat{e}(A) \leq 1$ for any $A \in F(X)$, and $\hat{e}$ satisfy Definition 2.1 as follows

(E1) $\hat{e}$ is zero for $\forall D \in P(X)$, hence satisfied.

(E2) $\hat{e}([\frac{1}{2}]) = \max_{A \in F(X)} \hat{e}(A)$ is also satisfied.

(E3) for $e(A^*) \le e(A)$, $\tilde{e}(A^*) \le \tilde{e}(A)$ is clear.

(E4) for $e(A) \le e(A^C)$, $\tilde{e}(A) \le \tilde{e}(A^C)$, is also easily proved, where $\forall A \in F(X)$. $Q.E.D.$

Hence the structure of theorem 2.1 satisfies the entropy which is induced from the another entropy.

III. Fuzzy entropy induced by distance measure

In this section, we propose entropy that is induced by the distance measure. Among distance measures, Hamming distance is commonly used σ-distance measure between fuzzy sets A and B,

$$d_H(A, B) = \frac{1}{n} \sum_{i=1}^{n} |\mu_A(x_i) - \mu_B(x_i)|$$

where $X = x_1, x_2, \cdots x_n$, $|k|$ is the absolute value of k. Next Proposition shows that the distance relation of between fuzzy set and crisp sets.

Proposition 3.1 (Fan and Xie, 1999). Let d be a σ-distance measure on $F(X)$, then

(i) $d(A, A_{near}) \ge d(A^*, A_{near})$

(ii) $d(A, A_{far}) \le d(A^*, A_{far})$.

Fan, Ma and Xie proposed the following theorem [7].

Theorem 3.1 (Fan, Ma, and Xie, 2001) Let d be a σ-distance measure on $F(X)$, if d satisfies

(i) $d(\frac{1}{2}D, [0]) = d(\frac{1}{2}D, D)$, $\forall D \in P(X)$,

(ii) $d(A^C, B^C) = d(A, B)$, $A, B \in F(X)$,

then $e(A) = D(A, A_{near}) + 1 - d(A, A_{far})$ is a fuzzy entropy.

Now we propose another fuzzy entropy induced by distance measure which is different from Theorem 3.1 of Fan, Ma and Xie [7]. Proposed entropy needs only A_{near} crisp set, and it has the advantage in computation of entropy.

Theorem 3.2 Let d be a σ-distance measure on $F(X)$; if d satisfies

$$d(A^C, B^C) = d(A, B), A, B \in F(X),$$

then

$$e(A) = 2d((A \cap A_{near}), [1]) + 2d((A \cup A_{near}), [0]) - 2 \quad (3)$$

is a fuzzy entropy.

Proof. The proposed equation in (3) become the entropy for the fuzzy set A if it satisfies Definition 2.1. Hence we start from (E1). For (E1), $\forall D \in P(X), D_{near} = D$, therefore,

$$\begin{aligned} e(D) &= 2d((D \cap D_{near}), [1]) + 2d((D \cup D_{near}), [0]) - 2 \\ &= 2d(D, [1]) + 2d(D, [0]) - 2 = 0 \end{aligned}$$

(E2) represent that crisp set 1/2 has the maximum entropy 1. Therefore, the entropy $e([\frac{1}{2}])$ satisfies

$$\begin{aligned} e([\tfrac{1}{2}]) &= 2d(([\tfrac{1}{2}] \cap [\tfrac{1}{2}]_{near}), [1]) \\ &\quad + 2d(([\tfrac{1}{2}] \cup [\tfrac{1}{2}]_{near}), [0]) - 2 \\ &= 2d(([\tfrac{1}{2}] \cap [1]), [1]) \\ &\quad + 2d(([\tfrac{1}{2}] \cup [1]), [0]) - 2 \\ &= 2 \cdot \tfrac{1}{2} + 2 \cdot 1 - 2 = 1 \end{aligned}$$

In the above equation, $[\frac{1}{2}]_{near} = [1]$ satisfied.

(E3) means that entropy of the sharpened version of fuzzy set A, $e(A^*)$ is less than or equal $e(A)$. For the proof, $A^*_{near} = A_{near}$ is also used.

$$\begin{aligned} e(A^*) &= 2d((A^* \cap A^*_{near}), [1]) + 2d((A^* \cup A^*_{near}), [0]) - 2 \\ &= 2d((A^* \cap A_{near}), [1]) + 2d((A^* \cup A_{near}), [0]) - 2 \\ &\le 2d((A \cap A_{near}), [1]) + 2d((A \cup A_{near}), [0]) - 2 \\ &= e(A) \end{aligned}$$

Inequality in the above equation is satisfied because of $d(A, A_{near}) \ge d(A^*, A_{near})$ in Proposition 3.1 (i). Finally, (E4) is proved using the assumption $d(A^C, B^C) = d(A, B)$, hence we have

$$\begin{aligned} e(A) &= 2d((A \cap A_{near}), [1]) + 2d((A \cup A_{near}), [0]) - 2 \\ &= 2d((A \cap A_{near})^C, [1]^C) \\ &\qquad + 2d((A \cup A_{near})^C, [0]^C) - 2 \\ &= 2d((A^C \cup A^C_{near}), [0]) \\ &\qquad + 2d((A^C \cap A^C_{near}), [1]) - 2 \\ &= e(A^C). \quad Q.E.D. \end{aligned}$$

Theorem 3.2 uses only A_{near} crisp set, hence we can consider another entropy. Which considers only A_{far}, and it has more compact form than Theorem 3.2.

Theorem 3.3 Let d be a σ-distance measure on $F(X)$; if d satisfies

$$d(A^c, B^c) = d(A, B), A, B \in F(X),$$

then

$$e(A) = 2d((A \cap A_{far}), [0]) + 2d((A \cup A_{far}), [1]) \quad (4)$$

is a fuzzy entropy.

Proof. In a similar way we can prove from (E1) to (E4). For (E1), $\forall D \in P(X), D_{far} = D^C$, therefore,

$$\begin{aligned} e(D) &= 2d((D \cap D_{far}), [0]) + 2d((D \cup D_{far}), [1]) \\ &= 2d([0], [0]) + 2d([1], [1]) = 0 \end{aligned}$$

And the entropy of crisp set $[\frac{1}{2}]$ is obtained as follows, hence (E2) is

$$\begin{aligned} e([\tfrac{1}{2}]) &= 2d(([\tfrac{1}{2}]\cap[\tfrac{1}{2}]_{far}),[0]) \\ &\qquad + 2d(([\tfrac{1}{2}]\cup[\tfrac{1}{2}]_{far}),[1]) \\ &= 2d(([\tfrac{1}{2}]\cap[0]),[0]) + 2d(([\tfrac{1}{2}],[0]),[1]) \\ &= 0 + 2\cdot\tfrac{1}{2} = 1. \end{aligned}$$

In this case $[\frac{1}{2}]_{far}=[0]$ is also used. Entropy between fuzzy set and sharpened version is derived for the proof of (E3), for the proof $A^{*}_{far}=A_{far}$ is also used. Property of Proposition 3.1 (ii) $d(A,A_{far})\le d(A^{*},A_{far})$ is used in inequality of following proof.

$$\begin{aligned} e(A^{*}) &= 2d((A^{*}\cap A^{*}_{far}),[0]) + 2d((A^{*}\cup A^{*}_{far}),[1]) \\ &= 2d((A^{*}\cap A_{far}),[0]) + 2d((A^{*}\cup A_{far}),[1]) \\ &\le 2d((A\cap A_{far}),[0]) + 2d((A\cup A_{far}),[1]) \\ &= e(A) \end{aligned}$$

(E4) is derived with the assumption $d(A^{C},B^{C})=d(A,B)$, we have

$$\begin{aligned} e(A) &= 2d((A\cap A_{far}),[0]) + 2d((A\cup A_{far}),[1]) \\ &= 2d((A\cap A_{far})^{C},[0]^{C}) + 2d((A\cup A_{far})^{C},[1]^{C}) \\ &= 2d((A^{C}\cup A^{C}_{far}),[1]) + 2d((A^{C}\cap A^{C}_{far}),[0]) \\ &= e(A^{C}). \quad Q.E.D. \end{aligned}$$

Proposed entropies Theorem 3.2 and 3.3 have some advantages to the Liu's, they don't need assumption (i) of Theorem 3.1 to prove (3) and (4). Furthermore (3) and (4) use only one crisp sets A_{near} and A_{far}, respectively. Later we check the proposed entropy of Theorem 3.2 and 3.3 are the σ-entropy on $F(X)$ for any $A\in F(X)$, satisfying $e(A)=e(A\cap D)+e(A\cap D^{C})$. Next, we apply Theorem 3.2 and 3.3 to detect reliable phase current among the 3-phases faulted induction motor.

IV. Illustrative Example

For the fault decision for the faulted motor 3-phase stator currents are given. The stator current is the only information that give the characteristics about what faults take place. Data from the induction machine, 220V, 3450 rpm, 4 poles, 24 bars, 0.5 HP motor have been used to verify the results experimentally. Six cases of bearing fault, bowed rotor, broken rotor bar static eccentricity, dynamic eccentricity and healthy conditions are given.

One phase current for the healthy and faulted signals at the full load are illustrated in Fig. 1. Input signal have 16,384 data points, respectively. Maximum frequency represents 3 kHz, data duration is 2.1333 s. As shown in Fig. 1, differences of the various signals are not easy to discriminate. Hence, we proceed with the useful Wavelet transformation to detect the characteristics of the 6 signals. Among 12 details, the 4th coefficients of the 6th detail shown in Fig. 2 has a good character to discriminate various faults. To get the most reliable information from the 3-phase stator currents, now we have to investigate another phase currents. After proceeding Wavelet transformation to the other two phase currents, we get 20 data for the 4th coefficients of the 6th detail, respectively.

To measure of the entropies of the each phases, we need to construct membership functions. With 20 data of the each phases, we generate 50 data that are the means of randomly chosen 10 data from original 20 data using the Bootstrap method. Then 50 data for the phase 1 from 6.0 ~7.1, 50 data for the phase 2 from 5.0 ~7.16, and 50 data for the phase 3 from 3.5 ~9.0 are obtained respectively.

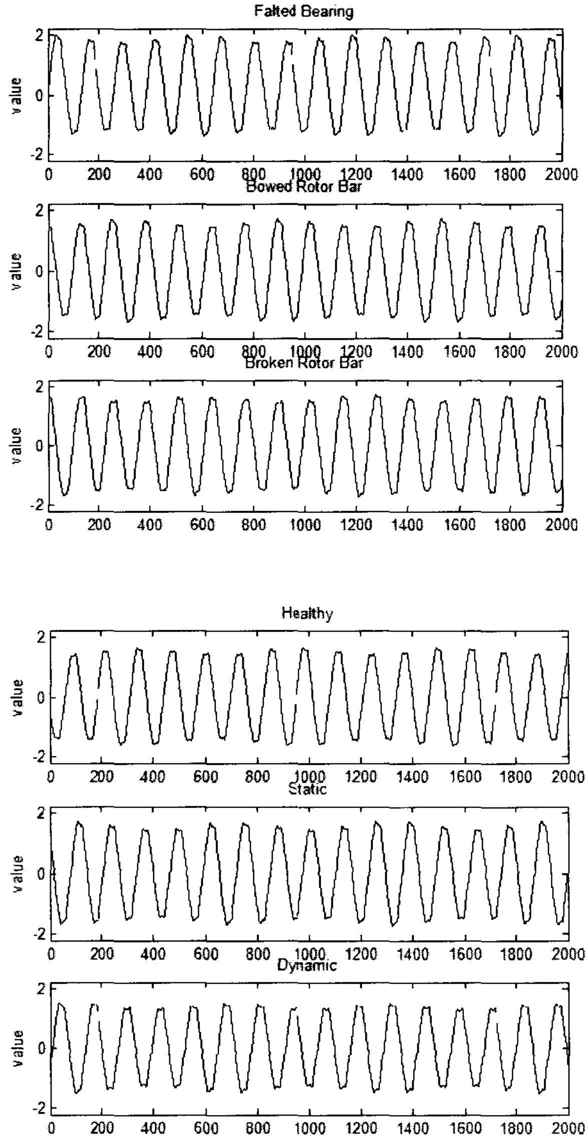

Figure 1 : Stator currents of healthy and faulted case.

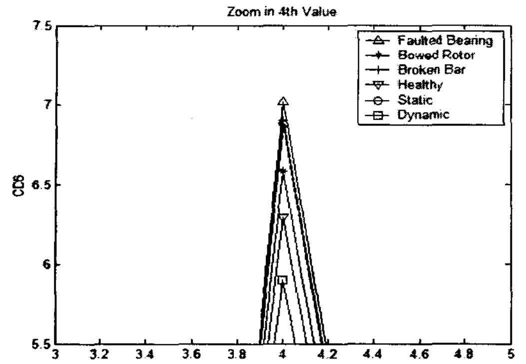

Figure 2: 4th coefficients of the 6th detail.

Now we construct Gaussian distribution with the 50 data, respectively (by the Central Limit Theorem). After normalizing, we consider three Gaussian functions as membership functions for the 3-phase currents, which are illustrated in Fig. 3, 4, and 5. For the computation of entropy, we assign center rectangle to the A_{near}, and the complement of A_{near} denotes A_{far}. By Theorem 3.2 and 3.3, we apply fuzzy entropy to the Fig. 3-5.

$$e(A) = 2d((A \cap A_{near}),[1]) + 2d((A \cup A_{near}),[0]) - 2 \quad (5)$$

$$e(A) = 2d((A \cap A_{far}),[0]) + 2d((A \cup A_{far}),[1]) \quad (6)$$

Table 1: Entropies of three phases

	Phase 1	Phase 2	Phase 3
theorem 3.2	0.62396	0.62504	0.62432
theorem 3.3	0.62396	0.62504	0.62432

with this membership functions, we can calculate the entropy measures of each phase currents. Table 1 indicates that 3-phase currents have similar entropies in Theorem 3.2 and Theorem 3.3. We can conclude that phase 1 is the most reliable among 3-phase currents. Next we derive the σ-entropies of (5) and (6). As noted in Definition 2.4, σ-entropy represents $e(A) = e(A \cap D) + e(A \cap D^c)$. Hence the structures of σ-entropies of (5) and (6) are

$$\begin{aligned} e(A) = {} & 2d(((A \cap D) \cap (A \cap D)_{near}),[1]) \\ & + 2d(((A \cap D) \cup (A \cap D)_{near}),[0]) \\ & + 2d(((A \cap D^c) \cap (A \cap D^c)_{near}),[1]) \\ & + 2d(((A \cap D^c) \cup (A \cap D^c)_{near}),[0]) - 4 \end{aligned} \quad (7)$$

$$\begin{aligned} e(A) = {} & 2d(((A \cap D) \cap (A \cap D)_{far}),[0]) \\ & + 2d(((A \cap D) \cup (A \cap D)_{far}),[1]) \\ & + 2d(((A \cap D^c) \cap (A \cap D^c)_{far}),[0]) \\ & + 2d(((A \cap D^c) \cup (A \cap D^c)_{far}),[1]) \end{aligned} \quad (8)$$

We obtain same results in Table 1 with (7) and (8) [17]. Hence the proposed entropies also satisfy σ-entropy.

V. Conclusions

We investigate the relations of entropy, distance measure and similarity measure. By the definition and results of Liu, we propose new entropy formula with the distance measure. For the faulted induction motor current signals, Wavelet transform have been carried out. Through the Wavelet transform, we can find the 4th value of 6th detail result from the 12 scales of wavelet decomposition is useful to analyze features of fault signals. Also the membership function of the 3-phase current signals are formulated using the Bootstrap method and Central Limit Theorem. Furthermore, the proposed entropy computation is obtained to the faulted induction machine, and the values of the entropies are illustrated.

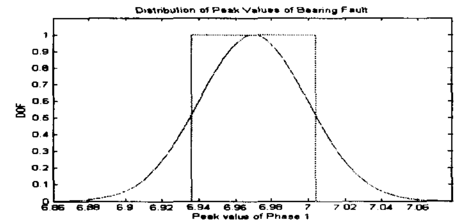

Figure 3: Membership function of phase-1 current.

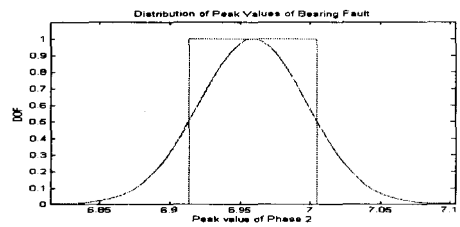

Figure 4: Membership function of phase-2 current.

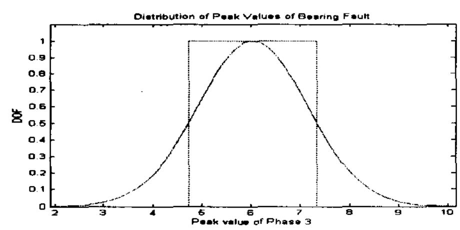

Figure 5: Membership function of phase-3 current.

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