Stator winding short-circuit fault diagnosis based on multi-sensor fuzzy data fusion

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***Abstract*—This paper uses data fusion based on fuzzy integral theory for stator winding inter-turn short circuit fault diagnosis in induction motors. Time-domain features are extracted from current signals, and a technique is proposed to choose appropriate features. The fuzzy c-mean analysis method is employed to classify different modes. It is used to choose the membership values of each feature for each fault mode. Finally, different features are fused at feature-level and decision-level using fuzzy integral data fusion to produce diagnostic results. Results show that fuzzy data fusion method performs very well for fault diagnosis in a 4hp laboratory induction motor.**

***Index Terms*— Data fusion, Fault diagnosis, Fuzzy integral, Stator three-phase current**

I. Introduction

INDUCTION motors are widely used in industry. Motors are exposed to various faults, caused by environmental conditions such as humidity, dust, etc. If these faults are not diagnosed in early stages, they may lead to failure in other parts of motor. Short-circuit defect in stator windings is a common fault accrued in induction motors. Stator winding fault accounts for 36% of all induction motor failures, and it is the most important electrical failure in induction motors [1]. Detection of this fault in its early stages is really important due to the increase of eddy current and the loss of windings insulation. Therefore, various methods which are based on models [2], signal processing [2,3], and intelligent methods [4] have been widely used in diagnosing this fault. In the proposed methods, mostly the information obtained from one signal is used for fault diagnosis which may in some cases result in misdiagnosis. One proposed approach to avoid this problem is information combination from different sources. The result obtained from data fusion is normally more reliable than those obtained from individual sensors. Data fusion can be performed in three different levels: data level, feature level, and decision level. The appropriate fusion level is chosen according to the fusion method and accuracy requirements [5]. In current paper, data fusion is performed in both feature and decision levels.

Various techniques have been applied for data fusion, for example data fusion based on estimation methods [6], classification methods [7], inference methods [8], artificial intelligence methods [7,9] and multiple methods. Fuzzy integral can be considers as a subset of artificial intelligence methods. It is somehow different from other methods, as it considers both the evidence supplied by each information source and the expected worth of each subset of sources in its decision making process. In addition, fuzzy measure reflects importance of each feature and interactions among features. Therefore fuzzy integral is a valuable tool in overcoming the inherent ambiguities present in any decision making system [10]. Many machinery faults have fuzzy nature, and the use of fuzzy techniques are thus appropriate for their fault diagnosis.

Vibration and temperature signals have been used to provide new monitoring techniques in the two past decades. However, these sensors are expensive and they should be carefully mounted on the motor. Some recent research works have been directed toward using electrical sensors such as current and voltage for condition monitoring [11].

In this paper the fusion of signals measured by electrical current sensors has been used for diagnosing induction motor stator windings short-circuit fault. For feature level fault diagnosis, after collecting feature sets, the fuzzy c-means (FCM) analysis method is employed to classify induction motor different modes, and it is used to identify the relation between a feature set and a fault prototype. Gained results are fused by the Choquet fuzzy integral and induction motor final mode is identified. For decision level fault diagnosis, the FCM algorithm is used for primary diagnosis of feature groups fault mode, and system final mode is identified by the Sugeno fuzzy integral. The results show the proposed method performs very well in fault diagnosis of a 4hp laboratory induction motor.

This paper consists of six sections. The second section explains the required math tools. Third section provides brief descriptions of fuzzy measure and fuzzy integral theories and their applications for fault diagnosis of induction motors. Data acquisition and feature extraction method are described in section 4. Results and discussion are presented in section 5.

II. Math Tools

A. Fuzzy C-mean

FCM algorithm is one of the most popular fuzzy clustering methods. FCM has been extensively used in various fields of research. The purpose of this unsupervised algorithm is classification of samples in predetermined groups. FCM divides samples to C predetermined clusters. Clusters are considered as

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fuzzy sets with various membership degrees in the interval $\begin{bmatrix}0 & 1\end{bmatrix}$. A membership degree shows the amount of belonging of each sample in each cluster. The membership value of each cluster is determined with the center of that cluster by minimizing the following cost function. FCM algorithm will be updated iteratively [12].

$$J_f(U,CC)=\sum_{m=1}^{M}\sum_{i=1}^{N}\sum_{j=1}^{C}U_{ijm}^{f}D_{ijm}^{2} \tag{1}$$

In (1) N is the number of samples, M is the input samples dimension, and C is the number of clusters. D_{ijm} is the Euclidean distance between i^{th} sample and j^{th} cluster center with m^{th} dimension. $U=\{U_{ijm}\}$ is the membership function matrix with values between zero and one. f shows the overlap between clusters and takes real values greater than 1. CC is the cluster center vector.

In this paper is used FCM clustering algorithm because of:

- In non-fuzzy clustering (also known as hard clustering), data is divided into distinct clusters, where each data point can only belong to exactly one cluster. In fuzzy clustering, data points can potentially belong to multiple clusters.
- Differs from the k-means objective function by the addition of the membership values and the fuzzifier.
- Gives best result for overlapped data set and comparatively better then k-means algorithm.
- Unlike k-means where data point must exclusively belong to one cluster center here data point is assigned membership to each cluster center as a result of which data point may belong to more than one cluster center.

B. *Fuzzy Measure and Fuzzy Integral*

Fig. 1. shows a multiclass neuron model of a fuzzy integral. In this figure $O=\{O_1,O_2,...,O_t\}$ is the set of information of different sources, and measurements are classified in $C_1,C_2,...,C_q$ classes. Let $X=\{x_1,x_2,...,x_n\}$ be a finite set which represents a set of n features of information sources.

Sugeno fuzzy measure $g_\lambda : P(X)\rightarrow\begin{bmatrix}0 & 1\end{bmatrix}$, where $P(X)$ is the power set of X, is a real-valued function that satisfies the following properties [10]:

- $g(\phi)=0$ and $g(X)=1$
- $g(A)\le g(B)$ if $A\subseteq B$
- If $A_i=\{x_1,x_2,...,x_i\}$ is an increasing sequence of subset of X, then $\lim_{i\to\infty} g(A_i)=g\left(\bigcap_{i=1}^{\infty}A_i\right)$

$$g_\lambda(A\cup B)=g_\lambda(A)+g_\lambda(B)+\lambda g_\lambda(A)g_\lambda(B)\ ;\lambda>-1 \tag{2}$$

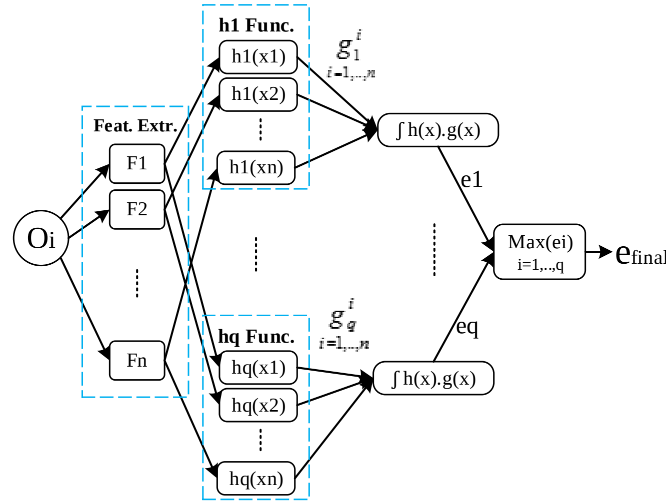

Fig. 1. Multiclass fuzzy neuron model

A conventional way of presenting fuzzy measure in the finite case is to use a network presentation. The network of the 2^n coefficients of the fuzzy measure is equivalent to the network of the power set element with respect to set inclusion relations. Fig. 2. is an example of the network when $n=4$.

Nodes of the network present subsets of power set or fuzzy measure coefficients, and links of the network present order relations based on '$\le$' for fuzzy measure coefficients. A fuzzy measure coefficient is always equal to zero in the first node, and equal to one in the last node. A path is set of chained links, starting from the first node (g_ϕ) and arriving to the last node (g_X). Therefore, the bolded path in Fig. 2. implies $x_3<x_2<x_4<x_1$. According to this path, the coefficients $g(\{x_1\})$, $g(\{x_1,x_4\})$ and $g(\{x_1,x_2,x_4\})$ are used in fuzzy integral [13].

A fuzzy density function is defined as $g^i=g_\lambda(\{x_i\})$. Fuzzy density value g^i is interpreted as the importance of the single information source x_i in any class. Solving the following equation leads to a polynomial in λ of degree n-1:

$$1+\lambda=\prod_{i=1}^{n}\left(1+\lambda g^i\right) \tag{3}$$

An approximation of λ can be obtained using Newton's method. Sugeno measure $g(A_i)$ is computed as:

$$\begin{aligned} &g(A_1)=g(\{x_1\})\\ &g(A_i)=g^i+g(A_{i-1})+\lambda g^i g(A_{i-1})\\ &\qquad ;1<i\le n \end{aligned} \tag{4}$$

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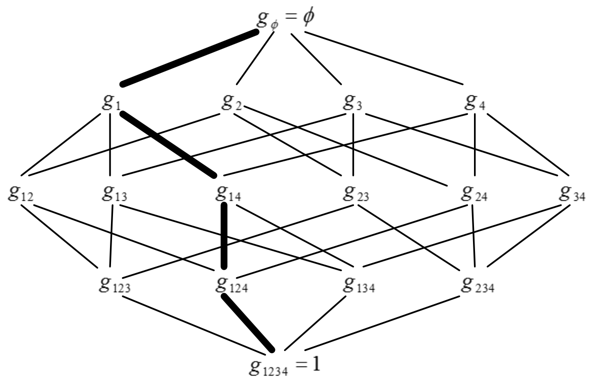

Fig. 2. The network of fuzzy measure coefficient for *n=4*

Sugeno and Choquet fuzzy integrals of a function $h : X \rightarrow [0 \quad 1]$ with respect to fuzzy measure g are defined respectively as follows:

$$\begin{aligned} S_g &= \int_A h(x) \circ g(\bullet) \\ &= \sup_{E \subseteq X} \left[\min\left(\min_{x \in E} h(x), g(A \cap E) \right) \right] \\ &= \sup_{\alpha \in [0,1]} \left[\min\left(\alpha, g(A \cap F_\alpha) \right) \right] \end{aligned} \tag{5.1}$$

$$\begin{aligned} C_g &= \int_A h(x) \circ g(\bullet) \\ &= \sum_{i=1}^{n} g(A_i) \left[h(x_i) - h(x_{i-1}) \right] \\ &= \sum_{i=1}^{n} h(x_i) \left[g(A_i) - g(A_{i-1}) \right] \end{aligned} \tag{5.2}$$

Suppose $h(x_{n+1}) = 0$ and $g(A_0) = 0$ in Choquet fuzzy integral, and $h(x_1) \geq \ldots \geq h(x_n)$ in both of them [10, 14].

III. Fuzzy Integral Fusion For Fault Diagnosis

Data fusion happens in different levels. In this part fuzzy data fusion is introduced for fault diagnosis in feature level and decision level based on FCM classification and Sugeno fuzzy measure.

A. *Feature-Level Fuzzy Integral Data Fusion for Fault Diagnosis*

Fig. 3. shows fault diagnosis using feature-level fuzzy integral data fusion. Stator three-phase current signals are divided into two sets of historical data and current condition monitoring data.

The first step is to gain a degree of partial matching, which reflects a degree of matching between each feature and each fault mode. Current condition monitoring data are used to identify partial matching of various features. Various methods such as the probability density function (pdf) exist for determining the degree of partial matching. In this paper, the FCM analysis method is used for this purpose. The degree of partial matching is determined using a degree of the fuzzy membership function using the FCM algorithm. The computation of fuzzy measure is needed after determining partial matching for the computation of fuzzy integral. For acquiring fuzzy measure which reflects the importance of each feature and the interactions among features, λ should be computed from (3), and the fuzzy density from the average of fuzzy membership degree for each feature per each fault mode. Training data (historical data) are used to identify fuzzy density of various features. Then according to (5), a degree of global matching is obtained. Fuzzy integral includes both the current confidence level and the overall confidence level per each feature and each fault mode [15, 16].

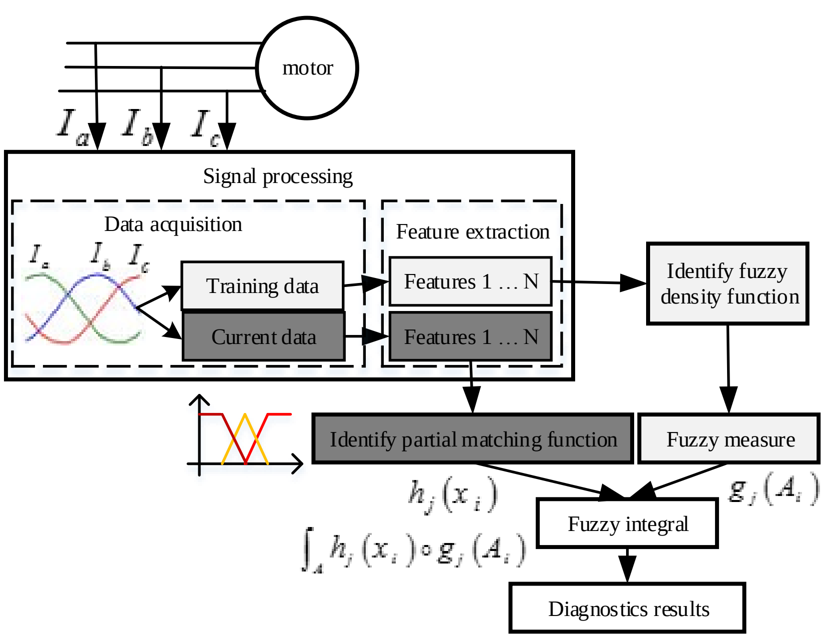

Fig. 3. Structure of feature level fault diagnosis model

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B. Decision-Level Fuzzy Integral Data Fusion for Fault Diagnosis

Fig. 4. shows fault diagnosis process using decision-level fuzzy integral fusion. The feature groups are entered into classifiers, and the output of the classifiers includes recognition rate and primary diagnosis results. Primary diagnosis results are obtained by current condition monitoring data. Then they are given a Fuzzy interpretation for providing a confidence level of classifiers for a given object and creating partial matching. These two sections are equal to creating partial matching in the feature-level fuzzy integral. The recognition rate shows the total ability of the classifiers in fault diagnosis which is usually obtained from statistical methods and training data (historical data). It is used as a fuzzy density for calculating fuzzy measure [15, 16].

IV. Experimental Result

A. Data Acquisition

In order for the proposed method to be realized, it was used for a short-circuit fault diagnosis in a 4hp induction motor stator windings. So as to create fault in the stator windings, the induction motor stator windings were extended out of the frame to simulate fault scenarios, as explained in TABLE I. To limit the short circuit loop current, a variable external resistor was connected between the taps of the shorted portion of the winding turns (see Fig. 5). An LA-55p current sensor was used to measure the induction motor's three-phase current signals, and the sampling data were transferred to a computer via the ADVABTECH PCI-1711 data card. The laboratory setup is shown in Fig. 6.

Data collection maximum frequency was 10KHz and thus 100000 data samples were collected. For improving the accuracy of data collection, this process was repeated 20 times for each mode. Fig. 7. shows the current signals for three different healthy/faulty scenarios.

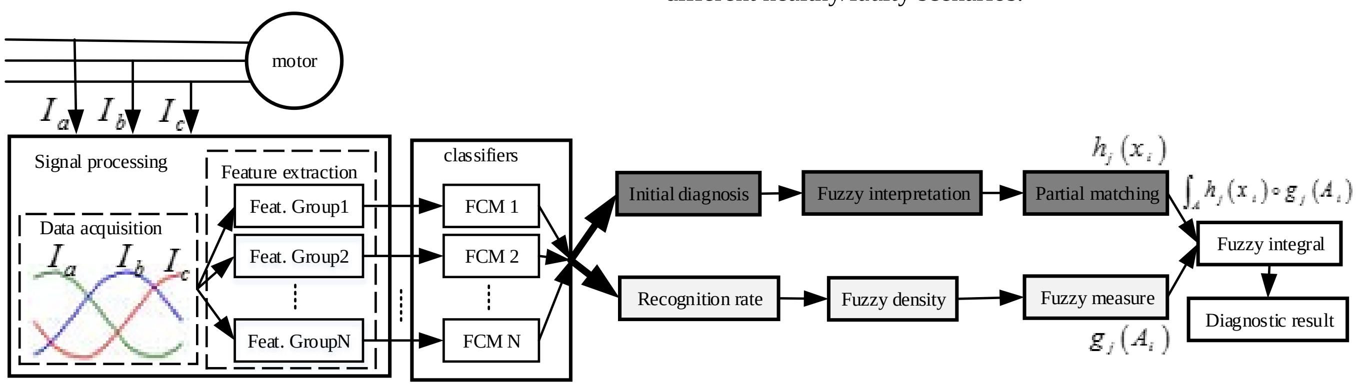


Fig. 4. Structure of decision level data fusion model

TABLE I
DESCRIPTION OF INDUCTION MOTOR FAULTS

Symbol	Fault kind
F_1	Free fault (healthy)
F_2	20% of winding stator is short circuit
F_3	15% of winding stator is short circuit
F_4	7% of winding stator is short circuit
F_5	10% of winding stator is short circuit
F_6	2% of winding stator is short circuit
F_7	5% of winding stator is short circuit

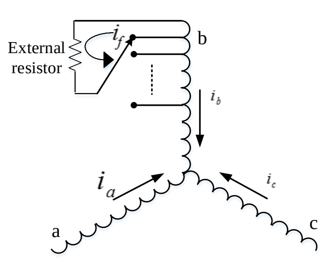
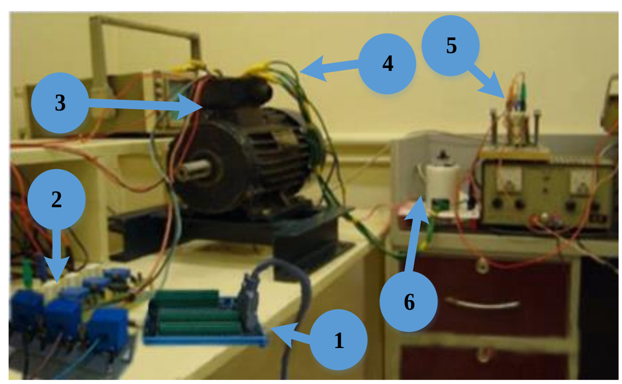


Fig. 5. Schematic diagram of stator windings fault



1. ADVANTECH PCI-1711 Data Card
2. LA-55p Current sensor
3. 4hp Induction Motor
4. Stator Windings
5. Potentiometer
6. Switch

Fig. 6. Laboratory setup

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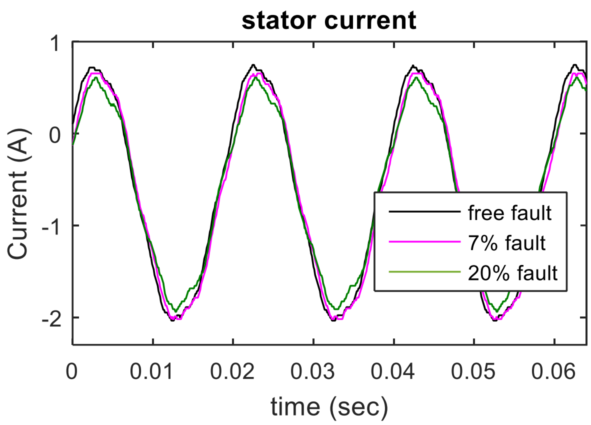

Fig. 7. Stator phase-a current in 3 different modes

B. *Features Calculation*

The features obtained in the diagnosis process by data fusion are very important and vital, because the correct mode detection of system depends on the quality of the measurement data and suitability of the features extracted from them.

In this paper, the statistical information of time-based data are used for obtaining the features of the measured signal. Features are calculated based on signal samples distribution. Lots of features are calculated based on the moments. If a change condition causes a change in the probability density function of the signal, then the moments may also change. Features are computed from moment coefficients including mean, standard deviation, skewness, and kurtosis:

$$C_1 = mean = \bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{6}$$

$$C_2 = Std. = \left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2\right)^{\frac{1}{2}}$$

$$C_3 = Skew. = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^3}{\left(\sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2}\right)^3}$$

$$C_4 = Kurt. = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^4}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2\right)^2}$$

As a measure of the uncertainty, first a histogram is estimated and then the entropy is calculated:

$$E_s(x) = Entr. = \ln\Delta - \sum P(x)\ln P(x) \tag{7}$$

Where Δ is the width of the histogram samples, x is a discrete time signal, and $P(x)$ is the distribution on the whole signal.

Finally, another important feature in time domain is the rms. Also, non-dimensional feature parameters in time domain are more popular, such as shape factor and crest factor:

$$rms = \sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2} \tag{8}$$

$$SF = \frac{x_{rms}}{\|x\|_\infty}$$

$$CF = \frac{x_p}{x_{rms}}$$

In (8), x_{rms}, $\|x\|_\infty$ and x_p are the rms value, absolute value and peak value, respectively [17].

The above features are calculated for stator three-phase current signals, and among them are extracted proper features and proper feature groups for system mode diagnosis.

C. *Feature Selection*

As mentioned above some features may not be useful and may even lead to misdiagnosis. Therefore, appropriate features are selected among the extracted ones.

In this paper, proper features are chosen based on partial matching recognition rate. The recognition rate is defined as the number of the correct modes detected per all the data for each mode.

In the decision level, a feature group consisting of 3 features is selected for each phase, and each feature group includes the feature set that has the largest recognition rate average over all system modes (TABLE II). In the feature level, first, amongst 8 features of each phase, 3 features that are proper (based upon the above algorithm for each mode and phase) are determined. Then amongst all the 9 selected features of three-phase, 5 features with higher recognition rates are selected for each fault mode (TABLE III). According to TABLE III, the features obtained from phases b and c include information that are more useful than those obtained from phase a, for different modes.

Fig. 8. shows the membership functions of the third feature group and the standard deviation feature, which are selected for all modes except for mode 6. The curves are obtained by fitting to Gaussian curves. As is evident from this figure, the membership functions of these features are similar to probability density functions which usually do not have normal distributions. The membership functions of the other feature groups and the other selected features are similar to those in Fig. 8.

TABLE II
SELECTED FEATURE GROUPS IN DECISION LEVEL

	Phase a	Phase b	Phase c
Feature groups	{CF., Std, Entr.}	{RMS, Std, Entr.}	{ Entr., Std, Kurt}

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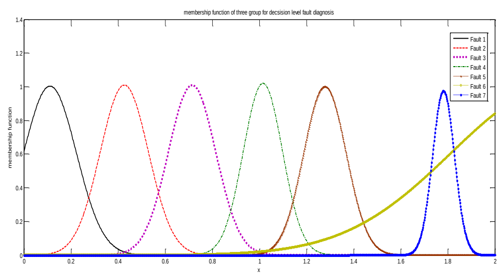
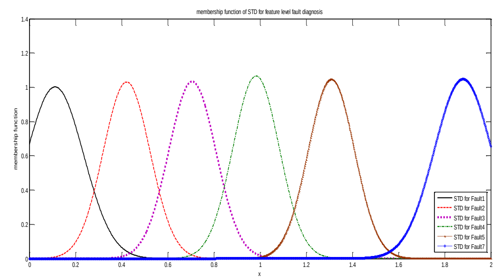
TABLE III
SELECTED FEATURES OF ANY PHASE AND ANY MODE IN FEATURE LEVEL

Fault mode	Phase a			Phase b			Phase c		
F_1	RMS	Entr.	Std.	Std.	RMS	Entr.	Std.	Kurt.	RMS
F_2	Std.	Entr.	Kurt.	Std.	Kurt.	RMS	Std.	CF.	Entr.
F_3	Std.	Mean	RMS	Std.	RMS	CF.	Kurt.	RMS	Entr.
F_4	SF.	Kurt.	RMS	RMS	Std.	Kurt.	Kurt.	SF.	Entr.
F_5	CF.	Kurt.	Entr.	RMS	Std.	SF.	Std.	CF.	Entr.
F_6	Entr.	Kurt.	RMS	CF.	Entr.	Mean	SF.	Kurt.	Entr.
F_7	SF.	Mean	Std.	Std.	Kurt.	RMS	CF.	Std.	Kurt



(a)



(b)

Fig. 8. Membership functions of selected features a) Membership functions of third feature group, b) Membership functions of Std

V. RESULT AND DISCUSSION

In the experiment process 70% of data was used for training and the remaining 30% for test. In this part, results from fuzzy integral are checked for both feature level and decision level.

A. Fault Diagnosis Based on Feature Level Fuzzy Integral Data Fusion

Fuzzy measure and partial matching enter the fuzzy integral according to Fig. 3. Seven fault modes are considered. Appropriate feature group is selected for each mode, so there are 7 feature groups. Choquet fuzzy integral is calculated for each feature group and finally, system final mode is found by multiplication rule.

TABLE IV. shows the fuzzy membership degree average and the average of fuzzy integral. Although some features have averages higher than the fuzzy integral averages, it can't be concluded that these features have higher diagnosis ability than the fuzzy integral. For example the two features of standard deviation and rms of phases b and c in first mode have higher average values than the fuzzy integral value, and this means that these four features have higher abilities in diagnosing the first mode of the system. However just using these features can't diagnose the correct modes of the system, because they show the correct mode of the system for F_1, and if another fault breaks out, these features may not correctly diagnose the system mode. The total average also implies the higher ability of fuzzy integral in correct diagnosis of the system modes.

B. Fault Diagnosis Based on Decision Level Fuzzy Integral Data Fusion

Initial diagnosis and fuzzy measure of classifications output enter the Sugeno fuzzy integral according to Fig. 4. The largest of fuzzy integral results show the system correct mode.

TABLE V. compares the recognition rate of classifiers and the fuzzy integral. According to this table, some classifiers do not have the ability to correctly diagnose the system modes, while the fuzzy integral diagnoses the correct mode of the system with a high confidence. For example, the first classifier cannot correctly diagnose the F_4 mode (7% short-circuit), while the fuzzy integral has the ability to correctly diagnose it with a recognition rate of 70%. This issue is evident in the total average of the recognition rate of each classifier and fuzzy integral.

The decision-level fuzzy integral has less informational bandwidth, less accuracy and less reliability compared to the feature-level fuzzy integral. Even though the decision-level fuzzy integral has managed to diagnose all system modes with a high recognition rate, it has a smaller diagnosis percentage. For example, according to TABLE V. in the F_5 mode (10% short-circuit), even though the decision level fuzzy integral has diagnosed this fault with the recognition rate of 100%, according to TABLE VI, its diagnosis percentage is 46% on average, while according to TABLE IV, this mode was diagnosed with the diagnosis percent of 94% using the feature-level fuzzy integral.

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TABLE IV
MEAN OF FUZZY MEMBERSHIP DEGREE AND FUZZY INTEGRAL IN FEATURE LEVEL

Fault mode	Membership degree mean Phase a			Phase b			Phase c			Fuzzy integral mean
F_1	RMS	Entr.	Std.	Std.	RMS	Entr.	Std.	Kurt.	RMS	0.96
	0.51	0.60	0.47	0.99	0.97	0.90	0.97	0.93	0.97	
F_2	Std.	Entr.	Kurt.	Std.	Kurt.	RMS	Std.	CF.	Entr.	0.96
	0.76	0.69	0.50	0.99	0.96	0.98	0.88	0.95	0.94	
F_3	Std.	Mean	RMS	Std.	RMS	CF.	Kurt.	RMS	Entr.	0.96
	0.82	0.75	0.60	0.99	0.99	0.88	0.91	0.97	0.88	
F_4	SF.	Kurt.	RMS	RMS	Std.	Kurt.	Kurt.	SF.	Entr.	0.89
	0.45	0.42	0.33	0.94	0.94	0.89	0.84	0.70	0.82	
F_5	CF.	Kurt.	Entr.	RMS	Std.	SF.	Std.	CF.	Entr.	0.94
	0.59	0.42	0.34	0.97	0.94	0.99	0.88	0.85	0.76	
F_6	Entr.	Kurt.	RMS	CF.	Entr.	Mean	SF.	Kurt.	Entr.	0.750
	0.52	0.44	0.47	0.79	0.74	0.65	0.81	0.59	0.60	
F_7	SF.	Mean	Std.	Std.	Kurt.	RMS	CF.	Std.	Kurt	0.84
	0.64	0.50	0.38	0.95	0.98	0.96	0.57	0.45	0.47	
Total mean		0.5337			0.8983			0.8203		0.9005

TABLE V
RECOGNITION RATE OF CLASSIFIERS AND FUZZY INTEGRAL IN DECISION LEVEL

		Fault mode F_1	F_2	F_3	F_4	F_5	F_6	F_7	total mean
Recognition rate of classifiers & fuzzy integral (%)	FCM 1	60	95	85	15	40	30	40	52.14
	FCM 2	100	100	100	90	30	80	85	83.57
	FCM 3	100	100	95	85	100	55	50	83.57
	Fuzzy integral	100	100	100	70	100	75	90	90.71

TABLE VI
MEAN OF FUZZY MEMBERSHIP DEGREE AND FUZZY INTEGRAL IN DECISION LEVEL

		Fault mode F_1	F_2	F_3	F_4	F_5	F_6	F_7
Mean of classifiers membership degree & fuzzy integral	FCM 1	0.57	0.83	0.81	0.19	0.36	0.29	0.39
	FCM 2	0.87	0.82	0.90	0.68	0.28	0.77	0.78
	FCM 3	0.99	0.89	0.88	0.77	0.99	0.52	0.47
	Fuzzy integral	0.75	0.73	0.76	0.42	0.46	0.42	0.53

VI. CONCLUSION

In this paper, short-circuit fault in induction motor stator windings was diagnosed using fuzzy data fusion in the two levels of feature and decision. Amongst the time features extracted from the stator three-phase current signals, proper features for fusion in each level were extracted according to the local diagnosis of the data based upon the proposed method.

In the feature-level fault diagnosis, fuzzy density was obtained by the membership functions obtained from the FCM algorithm, and fuzzy measure was calculated by fuzzy density. Also the local diagnosis of each feature was performed using fuzzy membership functions, and in the end, the final mode of the system was identified by applying feature local diagnosis and fuzzy measure to the fuzzy integral. In the decision level, feature groups were categorized by the FCM algorithm, and the initial diagnosis result of each feature group for each mode was decided. Then the fuzzy integral was used to combine initial results and create final decision.

Both of the proposed methods were tested on a laboratory induction motor for short circuit fault diagnosis. The results showed the capability of both proposed methods in separating the fault source, as these methods consider both the evidence supplied by each information source and the expected worth of each subset of sources in its decision making process.

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