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Hybrid time-frequency domain analysis for inverter-fed induction motor fault detection

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Hybrid Time-Frequency Domain Analysis for Inverter-Fed Induction Motor Fault Detection

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***Abstract*—The detection of faults in an induction motor is important as a part of preventive maintenance. Stator current is one of the most popular signals used for utility-supplied induction motor fault detection as a current sensor can be installed nonintrusively. In variable speeds operation, the use of an inverter to drive the induction motor introduces noise into the stator current so stator current based fault detection techniques become less reliable. This paper presents a hybrid algorithm, which combines time and frequency domain analysis, for broken rotor bar and bearing fault detection. Cluster information obtained by using Independent Component Analysis (ICA) to extract features from time domain current signals is combined with information extracted from fast Fourier transformed signal to reveal any underlying faults. To minimise the effect of the noise in the raw signal and intra-class variance in the extracted feature, a novel noise reduction approach– *Ensemble and Individual Noise Reduction* is employed. An advantage of the proposed scheme is that time domain analysis module can provide an early fault detection with minimal computation complexity. Experimental results obtained on the three-phase inverter-fed squirrel-cage induction motors demonstrated that the proposed method provides excellent classification results.**

***Index Terms*—Real-time fault diagnosis, inverter-driven induction motor, robust algorithm, hybrid time-frequency method.**

I. Introduction

Early detection of incipient motor faults is of paramount importance. Bearing and rotor related faults account for 40% and 10% of total induction motor failures respectively [1]. There is a significant amount of research effort on the preventive maintenance of motors. This includes the conventional vibration [2], [3] and thermal analysis [4] and the state of the art motor current signature analysis (MCSA) [5]–[8]. It has been suggested that stator current monitoring can detect the same fault indication as vibration monitoring without requiring access to the motor [6]. Although MCSA has been successfully applied in practice, it is comparatively more computationally intensive and required longer data trains than time domain fault detection and diagnosis techniques. Therefore, there has been increased interest in time domain analysis. A classical time domain analysis focuses principally on statistical characteristics of the signal such as peak level, standard deviation, skewness, kurtosis and crest factor. As the success of time domain analysis depends heavily on the availability of distinguishing features, fault diagnosis algorithms based on inputs obtained from transformation algorithms such as Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), and Independent Component Analysis (ICA) have been developed. Our earlier research on fixed supply-fed induction motor fault detection showed that the time domain approach is promising [9], [10]. Thus far, research has focused on induction motor running at fixed speed. In adjustable speed applications, AC induction motors are powered by inverters. Unlike a fixed supply-fed motor line current, the inverter-fed motor line current includes electromagnetic interference (EMI) noise that adversely affects the fault diagnosis algorithm. The inherent floor noise reduces the possibility of detecting the true fault pattern. Moreover, the current signal is always corrupted by noise originated from the high frequency switching components inside the inverter. It is reported that the noise can cause uncertainty when separating the healthy bearing pattern from the faulty unit [11]. Jung et al. [8] notice that the abnormal harmonics of bearing faults are in higher frequency bands than those of rotor faults. These bearing frequency bands may be close to or coincide with the noise bands. When the noise level is comparable with bearing fault signature amplitude, it is then very difficult to detect incipient bearing defects. Therefore, there is a need to have another measure to assist or confirm the existence of bearing fault when frequency domain analysis is carried out.

To address the need for robust monitoring of induction motors in variable speed applications, this paper introduces a novel hybrid time-frequency domain analysis method for detecting broken rotor bar and bearing faults in inverter-fed motors. In the following section, the MCSA technique which uses FFT spectrum analysis to detect broken rotor bar and bearing related faults will be introduced. Section III gives a brief introduction to Independent Component Analysis and explains how this analysis can be used to extract features from time domain signals. Due to the random stator current noise from the inverter-fed motor, a noise reduction algorithm known as *Ensemble and Individual Noise Reduction* (EINR) is employed in Section IV. The proposed hybrid algorithm is introduced in Section V while the experimental results in Section VI elucidate the effectiveness of the algorithm. Finally, conclusions are drawn in Section VII.

II. Motor Current Spectral Analysis

Among all the techniques in MCSA, the most classical and widely used technique is fast Fourier transform (FFT). FFT is an algorithm to compute the discrete Fourier transform (DFT) in a more efficient way. A FFT decomposes a sequence of values into components of different frequencies. A noiseless healthy motor current signal is a perfect sinusoidal wave. As there is no harmonics, we can only see one peak in the frequency spectrum. During actual operation, many harmonics will be present in the motor signal. Certain harmonics come from the supply and they are of little consequence. Thus, FFT spectrum will show many peaks including line frequency and its harmonics. This is known as the motor's current signature. Harmonics also generated from various electrical and mechanical faults. MCSA operates on the principle that the faults cause a change in the internal flux distribution, thus generating the harmonics.

A. Broken Rotor Bar Fault

In the current signature, the motor pole passing frequency will show up as a sideband to the line frequency. Broken rotor bar can cause anomaly in the magnetic field [6]. As the rotor bars start degrading, the rotor impedance rises. Due to this, the current drawn at the following sideband frequency rises

$$f_{brb} = f_s(1 \pm 2s) \tag{1}$$

where

f_s supply frequency;
s per-unit slip;

The presence of broken rotor bars is indicated by the difference in amplitude between the fundamental and the left sideband. The amplitude of the left sideband frequency component is proportional to the amount of broken rotor bars. As a general guide, it has been reported that a difference less than 50dB is a sign of broken rotor bar faults [6], [12]–[14].

B. Bearing Fault

Bearing faults can be divided into inner race, outer race, ball defect, or cage defect, which are the main sources of machine vibration. Inner or outer race are the two more common bearing faults. The mechanical vibrations in the air-gap can be considered as slight rotor radial displacements which result in air-gap eccentricity [11]. The relationship of bearing vibration to stator current spectrum results from the fact that any air-gap eccentricity produces anomalies in the air gap flux density [5]. The bearing related faults can be detected by determining the stator current spectral frequencies induced by characteristic vibration frequencies f_v. The induced current frequencies for bearing fault, f_{bng} given by

$$f_{bng} = |f_s \pm k f_v| \tag{2}$$

where $k = 1, 2, 3, \ldots$ are the harmonic indexes and f_v can be either inner race defect frequency, f_i or outer race defect frequency,f_o

$$f_{i,o} = \frac{n}{2} f_r \left[1 \pm \frac{bd}{pd} \cos\phi\right] \tag{3}$$

where

n number of bearing balls;
f_r mechanical rotor speed in Hz;

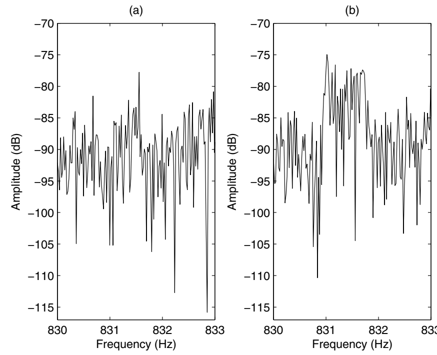


Fig. 1. Uncertain bearing frequencies components between (a) healthy motor (b) motor with inner race bearing fault. Due to the noise, the amplitude difference between two classes are less obvious.

bd ball diameter;
pd bearing pitch diameter;
ϕ contact angle of the balls on the races.

Fig. 1 compares the bearing frequency components for healthy motor and motor with inner race bearing fault. It is noticed that the amplitudes information can be uncertain due to the noise level or baseline drifting as mentioned in Section I. Unlike broken rotor bar fault whereby only left sideband needs to be monitored, notice that (2) have unspecified bearing fault harmonic numbers (k=1,2,3,...). Dominant harmonic (specific k) must be identified in order to detect the faults. Jung et al. [8] proposed a frequency auto search algorithm to search for the most dominant harmonic.

III. Independent Component Analysis

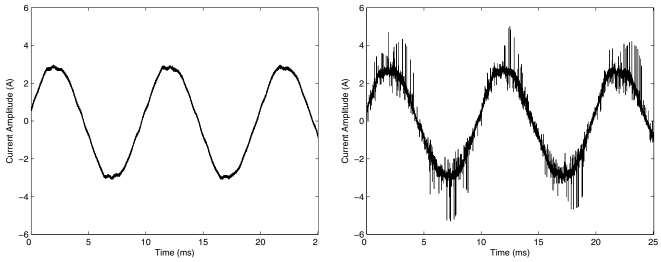
Independent Component Analysis (ICA) is a statistical technique for decomposing a complex dataset into independent sub-parts. In other words, ICA is a technique that represents a multidimensional random vector as a linear combination of nongaussian random variables ('independent components') that are as independent as possible. ICA problem can be formulated as

$$\mathbf{s} = \mathbf{W} \bullet \mathbf{x}. \tag{4}$$

where $\mathbf{x} = (x_1, x_2, \ldots, x_m)^T$ is an observed m-dimensional random vector , $\mathbf{s} = (s_1, s_2, \ldots, s_n)^T$ is an n-dimensional (latent) random vector whose components are assumed mutually independent, and $\mathbf{W}$ is the transformation matrix. The most widely used algorithm for estimating $\mathbf{W}$ is FastICA algorithm [15]. In pattern classification problem, the transformation can be considered as feature extraction whereby s_i is the coefficient of the i^{th} feature in the observed data vector $\mathbf{x}$. To overcome the curse-of-dimensionality, it is always feasible to have low-dimensional data (i.e., $i \leq 3$). For example, if two-dimensional input $\mathbf{s} = (s_1, s_2)^T$ is needed, then transformation matrix $\mathbf{W}$ dimension is chosen to be $2 \times m$.

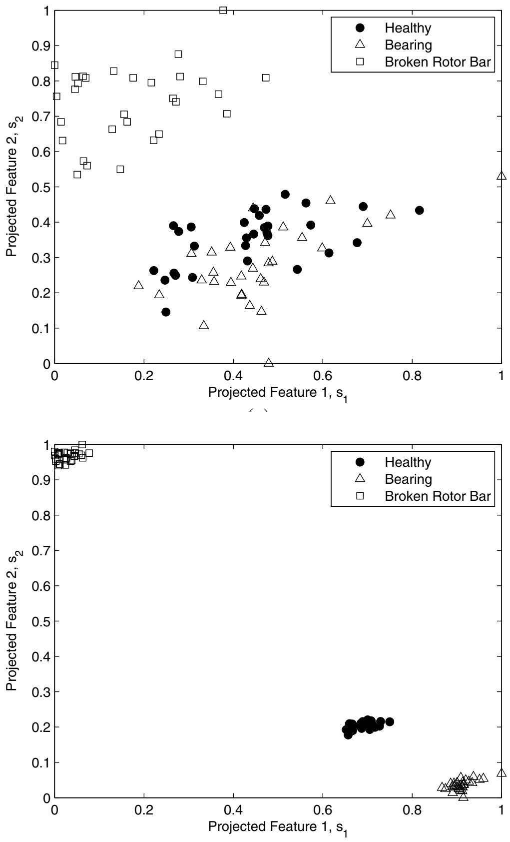
IV. Ensemble and Individual Noise Reduction

The preliminary work on using ICA to extract time domain features is very successful on fixed supply-fed induction motor as mentioned in Section I. Therefore, there is a strong interest to extend this technique to inverter-fed induction motor.



(a) (b)

Fig. 2. 50Hz Stator current signal from the (a) fixed supply-fed induction motor (b) inverter-fed induction motor.



(b)

Fig. 3. Scatter plot of the Independent Component Analysis (ICA) extracted 2-D features for inverter-fed motor (50Hz) (a) without *Emsemble and Individual Noise Reduction* (EINR) technique, and (b) with EINR technique.

However, the experimental data in Fig. 2 shows that the stator current from inverter-fed motor has relatively higher noise. As a result, the clusters corresponding to different motor conditions overlap with each other in the ICA feature space as shown in Fig. 3(a). In view of this, a noise reduction method known as *Ensemble and Individual Noise Reduction* (EINR) is employed to overcome the noise problem in inverter-fed motor stator current. Fig. 4 shows the procedures involved in EINR. Since noise is a random event, it is possible to reduce the noise by averaging a predetermined number of corrupted signals. Denote $(x(t), x(t+T), \ldots, x(t+(N-1)T))$ as a set of aligned periodic noisy base signals from the same source where N is the number of signals and T is the length of the signal, the first step is to compute the profile signal, $P(t)$ which is the summation of all the noisy base signals

$$P(t) = \sum_{k=0}^{N-1} x(t+kT). \tag{5}$$

It is clear from Fig. 4 that most of the noises have been eliminated in the profile signal. In the next step, for every incoming noisy signal $y(t)$, the denoised signal $\hat{y}(t)$ can be computed with the following equation

$$\hat{y}(t) = \frac{P(t) + y(t)}{(N+1)}. \tag{6}$$

In this way, the denoised signal shares the common profile yet retains its own information. The merit of this unique noise reduction method is that it can minimise the intra-class variation. In other words, as long as there are differences in the "profiles" from different classes, then the data will form well separated clusters in the feature space. Fig. 3(b) depicts the effect of applying EINR technique with parameters $N = 15$ and $T = 25000$. The overlapping problem has been solved.

V. Proposed Algorithm

The literature survey in Section I indicates that the MCSA approach to detect bearing related faults can be difficult when the noise amplitude is comparable to the bearing fault frequency component. On the other hand, the time domain projection using ICA algorithm has been shown to give promising results by producing distinctly separated clusters in 2-D feature space for fixed supply-fed induction motor. However, as shown in Fig. 7, the clusters are not invariant to speed in inverter-driven motors (i.e., the locations of the clusters vary with respect to different operating frequencies). Therefore, the decision boundaries are not fixed for all speeds. For these reasons, a hybrid time-frequency domain analysis that aims at increasing the robustness of the frequency domain analysis by utilising the cluster information obtained from time-domain feature projection is proposed. This hybrid approach enables the advantages of time and frequency domain analysis to complement each other for the needs of different application. The architecture of the proposed fault diagnosis system in Fig. 5 shows that motor condition monitoring is achieved by using a fuzzy system to fuse time and frequency domain features of the motor stator current. First, ICA is used to project time domain current signals into a 2-D feature space in order to extract distance information about a new input from the healthy cluster. On the other hand, frequency domain analysis is performed by computing the FFT spectrum and extracting the abnormal harmonics amplitudes. By using fuzzy logic to combine the extra information provided by the time-domain feature with the MCSA, more robust fault diagnosis can be achieved. In addition, the time domain feature can be used as a computationally simple early warning system for the presence of faults. Since time domain analysis requires much shorter segment of data and is computationally simpler than

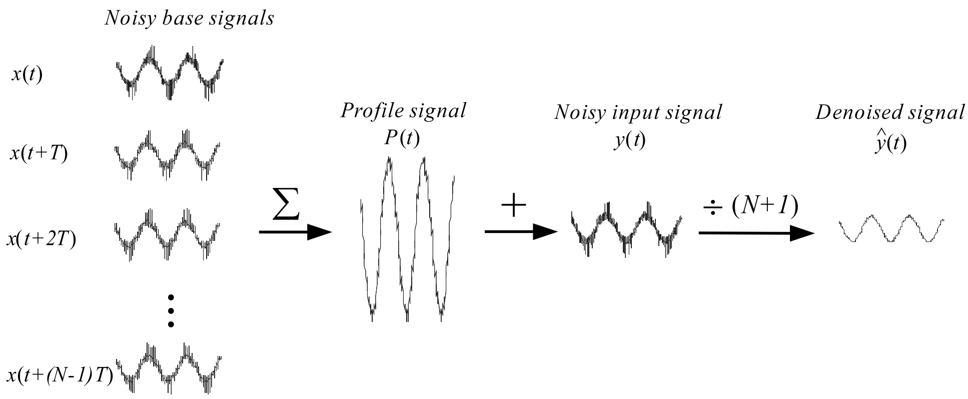


Fig. 4. Ensemble and individual noise reduction procedures.

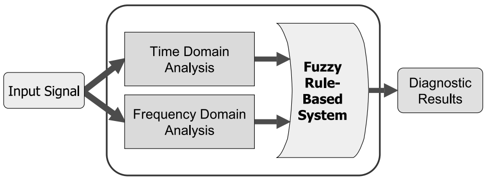


Fig. 5. Overview of the proposed hybrid time-frequency domain analysis algorithm.

FFT, it provides the possibility of detecting the presence of a fault quickly and efficiently. Any abnormal condition will be presented as an outlier to the healthy cluster in the feature space. Details of the hybrid algorithm are further depicted in Fig. 6.

A. Data Requirement and Processing

Before the raw stator current signal can be used, the signal must be preprocessed to remove the unwanted noise using the EINR approach described in Section IV. In order to compute FFT analysis, the length of the signal must be long enough (typically $>$ 20s depending on the sampling rate) to provide sufficient resolution to detect frequency components corresponding to the various fault conditions. While the lengthy signal is required for FFT analysis, the number of data points is enormous for ICA feature extraction in time domain. Therefore, for time domain analysis only one cycle of the signal will be used. This can reduce the computation time tremendously so as to provide faster response.

B. Commissioning Phase

The commissioning phase involves both time and frequency domain analysis as well as finding the parameters for the fuzzy rule-based classifier.

1) Time Domain: For time domain analysis, a single cycle of current signal (one cycle signal in Fig. 6) is discretised into the predetermined number of data points, T. For unbiased training, equal number of data sets are collected from healthy and faulty motor. From ICA analysis, the two most dominant independent components $\mathbf{w}_1$ and $\mathbf{w}_2$ will be recorded. The resultant transformation matrix $\mathbf{W}$ is a $2 \times m$ matrix, $\mathbf{W} = [\mathbf{w}_1 \mathbf{w}_2]^T$, where m is the length of the signal. ICA only needs to be computed once as the ICs stored in $\mathbf{W}$ can be used repeatedly to extract other signals with different frequencies.

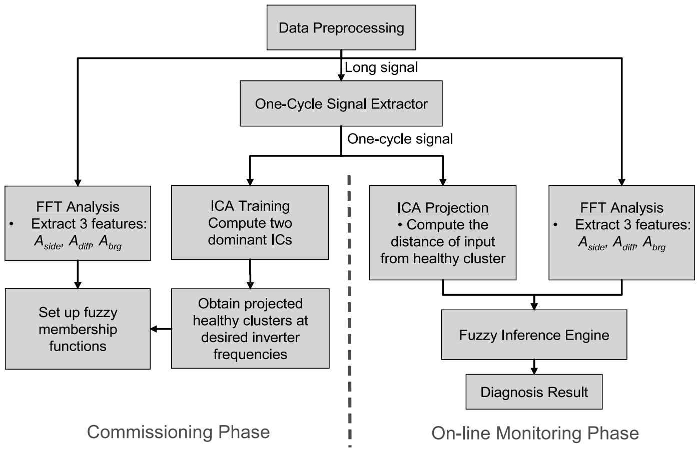


Fig. 6. Details of the proposed hybrid time-frequency domain analysis algorithm.

Fig. 7 shows that the healthy clusters are very compact, hence by measuring the distance of the incoming data from the healthy cluster during the testing phase, one can decide if the signal is faulty or not. In particular, a faulty signal will be clearly shown as an outlier. Thus in time domain analysis, the Euclidean distance information (d) extracted using the following equation is used as one of the inputs to the fuzzy rule-based classifier to provide quick diagnosis

$$d = \sqrt{(s_1 - \bar{s_1})^2 + (s_2 - \bar{s_2})^2} \quad (7)$$

where $(\bar{s_1}, \bar{s_2})$ is the centroid of the healthy cluster.

2) Frequency Domain: The frequency domain features are extracted from the FFT spectrum generated from the raw signal (long signal in Fig. 6). The components at the broken rotor bar frequency, f_{brb} and the bearing fault frequency, f_{brg} will be examined. There are three features to be extracted. The first feature is the amplitude of the left sideband, A_{side} while the second feature is the amplitude difference of the fundamental component and left sideband, A_{diff}. Both features are used to detect the existence of broken rotor bar. The third feature is the amplitude of the bearing fault component, A_{brg}. Since the signatures of the various types of bearing faults occur at different frequencies, A_{brg} is selected as the most dominant frequency component as extracted by the frequency

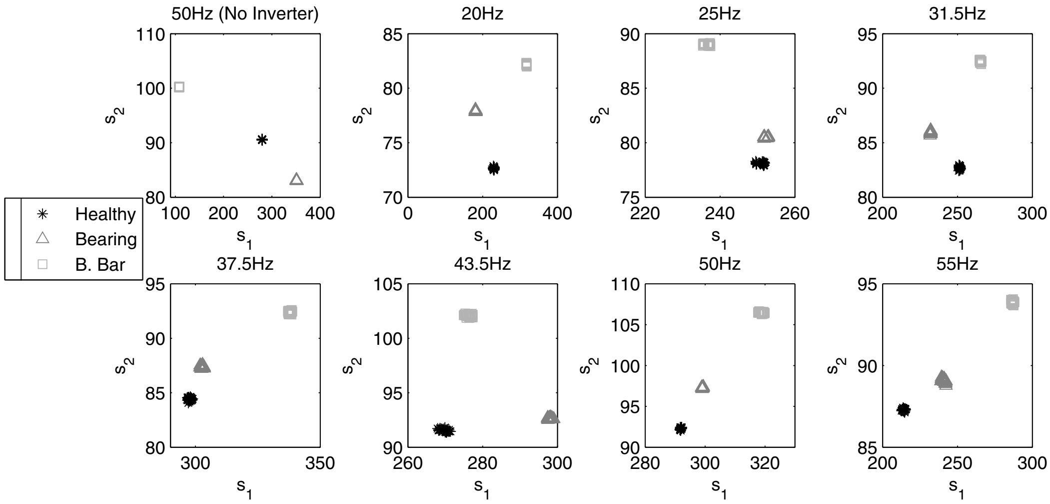


Fig. 7. Healthy and faulty clusters (bearing and broken rotor bar) for variable inverter frequencies during training stage except the left top one for fixed supply frequency. Each cluster contains 30 training data points.

auto search algorithm [8].

3) Fuzzy Rule Base: A fuzzy rule-based system allows experts' knowledge to be incorporated through intuitive *if-then* rules. The numerical data are represented as linguistic information which are in fact a set of fuzzy membership functions. The following rules are used to classify healthy motor and motor with bearing fault or broken rotor bar fault

R_1: If A_{side} is *small* and A_{diff} is *large* and A_{brg} is *small* and d is near, then STATUS is *Healthy*

R_2: If A_{side} is *small* and A_{diff} is *large* and A_{brg} is *large* and d is far, then STATUS is *Bearing Fault*

R_3: If A_{side} is *large* and A_{diff} is *small* and A_{brg} is *small* and d is far, then STATUS is *Broken Rotor Bar*.

Product t-norm and Max t-conorm are used to perform the fuzzy inferencing in this study. The diagnosis result is determined by the rule with the highest firing level, based on winner-takes-all strategy. Each of the antecedent set is a sigmoidal membership function and is characterised by two parameters a and c as shown in (8). Each universe of discourse has two fuzzy partitions.

$$f_{sig}(x) = \frac{1}{1 + e^{-a(x-c)}}. \tag{8}$$

For distance membership function, the parameter c in (8) is made adaptive with respect to the motor speed and is determined by

$$c = \tau \times d_{\bar{H}-\bar{F}} \tag{9}$$

where $\bar{H}$ is the centroid of the healthy cluster, $\bar{F}$ is the centroid of the nearest faulty cluster and $0 < \tau < 1$ is a threshold that controls the radius of the healthy cluster boundary. If $\tau \approx 0$, the incoming data must be very close to the healthy cluster centroid to be considered as a healthy signal. In contrast, for $\tau \approx 1$ the incoming data is still considered as a healthy data even its distance is nearer to faulty cluster than the healthy cluster. In other words, the parameter τ determines the separation needed for a data point to be considered as an outlier (i.e., faulty data). In a more critical application, τ can be set to a smaller value ($\tau \leq 0.5$) to avoid the false classification of a faulty motor as a healthy motor. The rest of the fuzzy membership function parameters are determined manually based on the observations during feature extraction steps.

C. On-line Monitoring Phase

During the on-line monitoring phase, pre-processing of the motot stator current into both time and frequency domain data are conducted in a manner similar to the commissioning phase. The single cycle ("short") test stator current input vector is projected onto the 2-D feature space using the pre-trained ICA transformation matrix $\mathbf{W}$. As mentioned earlier, the distance of projected test input from the healthy cluster provides a measure of how similar the signal is to the healthy signal. If the distance is small, then the signal likely belongs to the healthy class. Otherwise, it probably belongs to the faulty class. For frequency domain analysis, three amplitude features are extracted from the FFT spectrum of each incoming "long" test data sequence. The extracted distance and amplitude information are then fuzzified as fuzzy singletons and fed into the fuzzy rule-based classifier with the membership functions designed during the commissioning phase. Finally, the fuzzy inference engine gives the diagnosis result based on winner-takes-all principle.

VI. Experimental Results and Discussion

The proposed algorithm is tested on three identical motors. The technical specifications of the motor and its bearings are given in Tables I and Table II respectively. Two motors are artificially modified in which one of them has dent on the inner race while the other has two holes drilled on the rotor bar. All induction motors are driven by a voltage-fed pulse-width modulated inverter at variable frequencies. Segments of raw stator current is collected using a digital oscilloscope at the sampling rate of 20 kHz for 50 seconds. Since the motor is connected to an inverter, its speed is variable. In this study, the inverter is set to seven speeds: 20Hz, 25Hz,

TABLE I
RATED PARAMETERS OF THE INDUCTION MOTOR UNDER STUDY

Power	1.1kW
Voltage ($\triangle$/Y)	230/400V
Current ($\triangle$/Y)	4.5/2.6A
Frequency	50Hz
Speed	1410rpm
Pole pairs	2

TABLE II
BEARING PARAMETERS

Ball diameter, bd	8.89mm
Bearing pitch diameter pd	38.5mm
Number of bearing balls, n	13
Contact angle, ϕ	0°

31.5Hz, 37.5Hz, 43.5Hz, 50Hz and 55Hz. At each inverter frequency setting, 30 signal segments are collected for each class and used for training phase. On the other hand, the classification accuracy of the proposed algorithm is tested by 150 samples (50 segments of stator current data for each class). The one-cycle stator current signal which is processed by ICA projection has 360 data points. A "long" signal segment, containing 1×10^6 data points, is used to generate the FFT spectrum in order to provide sufficient resolution to detect abnormal current signature. From the FFT spectrum, the frequency domain parameters (A_{side}, A_{diff} and A_{brg}) can be extracted. The bearing fault frequencies are difficult to obtain as there are unspecified harmonic number in (2). By applying the frequency auto search algorithm [8], the most dominant harmonic frequency is found at $k = 2$ and $f_v = f_i$. Table III shows the classification results of the proposed hybrid algorithm obtained by using 0.5 as the Euclidean distance threshold, τ in (9) that controls the radius of the healthy cluster boundary. All 150 test samples are classified correctly. The results demonstrate that the combination of time and frequency domain analysis can give excellent classification results. A feature of the proposed hybrid approach is that the data length (360 data points per signal) and computational requirement for ICA projection is less demanding than the long signal used for FFT analysis (1×10^6 data points per signal). Consequently, in applications where motor condition monitoring need to be performed using less sophisticated hardware, the Euclidean distance data from ICA projection of the time domain data can be used to provide a quick, but rough, determination of the motor condition.

VII. CONCLUSION

This paper presents a methodology for the diagnosis of broken rotor bar and bearing faults for inverter-fed induction motor by making use of features extracted from time and frequency domain analysis. One advantage of the proposed hybrid algorithm over the conventional motor current signature analysis approach is that the classification accuracy is more robust against the uncertainties in the extracted features. Moreover, the algorithm can be made modular whereby the cluster information obtained from the time domain ICA analysis of the motor stator current carried out as a quick initial test to identify abnormal signal as an outlier before proceeding with the more computationally complex frequency domain analysis to identify the types of faults. Although results presented here are tested on motors with broken rotor bar and bearing related faults, the proposed hybrid method should be extendable to more fault classes.

TABLE III
PROPOSED HYBRID ALGORITHM PERFORMANCE

Class	Diagnosis Accuracy (%)
Healthy	100
Bearing	100
Broken Rotor Bar	100

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