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Online fault detection of induction motors using independent component analysis and fuzzy neural network

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Online Fault Detection of Induction Motors Using Independent Component Analysis and Fuzzy Neural Network

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Abstract— **This paper proposes the use of independent component analysis and fuzzy neural network for online fault detection of induction motors. The most dominating components of the stator currents measured from laboratory motors are directly identified by an improved method of independent component analysis, which are then used to obtain signatures of the stator current with different faults. The signatures are used to train a fuzzy neural network for detecting induction-motor problems such as broken rotor bars and bearing fault. Using signals collected from laboratory motors, the robustness of the proposed method for online fault detection is demonstrated for various motor load conditions.**

Index Terms— **Online Fault Detection, Induction Motors, Independent Component Analysis, Fuzzy neural network**

I. INTRODUCTION

Equipment failure leads to the loss of productivity or even human lives. Proper maintenance strategies are very desirable for minimizing operating and maintenance costs of energy systems without sacrificing reliability. Condition-based maintenance has largely replaced time-based maintenance due to the potential economic benefits of the former, where apparatus is maintained according to its working conditions, as evaluated by appropriate methods for continuous monitoring or periodic inspections to provide early warnings against failure [1-4]. Induction motors are an indispensable part of industries. The early detection of anomalies in electrical or mechanical parts of induction motors is important for the safe and economic operation of industrial processes.

One popular technique for online monitoring or periodic inspections on induction motors is stator current analysis, which is well known for providing continuous monitoring in a nonintrusive way [5]. Analysis of fault features from such signals is effective, as stator currents of running induction motors with different faults will show some kinds of difference from that in normal condition [6]. This is because different faults affect the running of the motor in different ways [7-8]. The stator current monitoring is thus viewed as an important fault detection scheme without requiring special access to the motor [6-8]. Bearing fault and broken rotor bars are two main types of faults of induction motors, and signature analysis for detecting these faults had been reviewed [6]. Most research works were performed by decomposing and analyzing the stator current using various methods such as: Fourier analysis, wavelets, neural networks, model-based techniques, and other statistical analysis [9-13]. The accuracy of these algorithms depends on the clarity and quantity of the data provided [14].

Independent Component Analysis (ICA) is a fascinating computational method for separating a multivariate signal into additive subcomponents supposing the mutual statistical independence of the non-Gaussian source signals [28-30]. It is a special case of blind source separation, and has many practical applications. It has received great attention in a variety of areas such as image processing [15-16], biomedical engineering [17] and load estimation of power systems [18]. Our previous work [19] employed ICA to perform reliable insulation diagnosis and online source recognition of partial discharge for gas insulated substations. However, there are only a limited number of publications on the application of ICA to fault detection of induction motors.

The trend in varying applications has been to automate the analysis of the measured signals by incorporating expert systems or neural networks into the online monitoring schemes to detect only single fault condition [5, 34]. There are many researchers studying the fault classification or diagnosis using fuzzy neural network (FNN). FNN has been used in detecting weld defects [20], fault diagnosis of power transformers [21], and other classification problems [22-27]. Employing FNN to detect or classify motor faults is rarely reported.

This paper exploits the ability of ICA for extracting the intrinsic features of the signals to compress the signals to a smaller working set [19]. It also exploits the classification ability of FNN [25-27] for handling uncertainties. An integration of these two techniques is thus proposed for detecting and classifying the bearing fault and broken rotor bar of induction motors. The procedure of the proposed scheme is shown in Fig. 1. ICA is employed to analyze the stator current and to compute the healthy and faulty motor signatures using the stator current waveforms collected from laboratory motors. These signatures are further analyzed by FNN for fault detection of induction motors. Experiment results show that the proposed method is robust and effective.

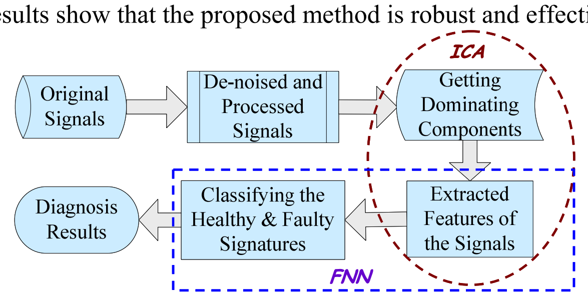

Fig. 1 Layout of the Proposed Scheme

This paper is organized into six sections. Section 2 outlines the proposed scheme and presents the setup of fault detection, classification and monitoring on laboratory motors. Section 3 describes the ICA technique used for healthy and faulty current analysis, followed by the classification procedure of FNN presented in Section 4. In Section 5, the results of healthy and faulty signatures under no load are discussed and compared with results obtained under varying loads. The robustness and performance of this method demonstrate the potentials of the proposed approach for the online fault detection and diagnosis of industrial motors. Section 6 concludes the paper.

II. LAYOUT OF PROPOSED SCHEME AND EXPERIMENTAL SETUP

A. Layout of the Combined ICA and FNN Scheme

As shown in Fig.1, the independent component features extracted by ICA are inputted to train the FNN and tune its parameters and structure and provide classification of induction-motor faults.

B. Experimental Setup

Fig. 2 shows the experimental setup for collecting healthy and faulty stator current waveforms from one healthy motor, one motor with broken rotor bars, and one motor with faulty bearing. The three motors are of the same model, being 3-phase 4-pole and rated at 1.1KW, 420 V and 50 Hz. During test, each motor drives a DC generator loaded with a variable resistance. The stator currents are sampled by a digital oscilloscope at a frequency of 500MHz.

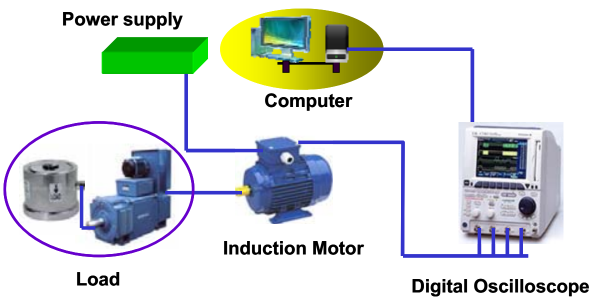

Fig. 2 Laboratory Setup for Fault Detection & Classification of Induction-motor Faults

III. HEALTHY & FAULTY CURRENT ANALYSIS BY ICA

A. Principle of ICA

ICA is a method to find underlying factors or components from multivariate statistical data [28]. One of the promising applications of ICA is feature extraction [19]. The popular way of formulating the ICA algorithm is to consider the estimation of the following generative model from the data [28-31]

$$x = As \tag{1}$$

where x is an observed m-dimensional vector, s is an n-dimensional random vector whose components are assumed mutually independent, and A is a constant $m \times n$ matrix to be estimated. It is usually further assumed that the dimensions of x and s are equal.

Taking a set of measured signal vector, x, and extracting from them a set of statistically independent components, y, thus the ICA problem is formulated as [31]

$$y = Wx \tag{2}$$

The matrix W, defining the transformation matrix, is then obtained as the inverse of the estimate of the matrix A.

It is particularly interesting to express mutual information I using negentropy, constraining the variables to be uncorrelated [29, 33 & 35]:

$$I(y_1, y_2, \ldots, y_n) = J(y) - \sum_i J(y_i) \tag{3}$$

The definition of negentropy, J, is given by

$$J(y) = H(y_{gauss}) - H(y) \tag{4}$$

where y_{gauss} is a Gaussian random variable with the same covariance matrix as y.

Because mutual information is the information-theoretic measure of the independence of random variables, it is naturally used as the criterion to obtain the decomposition in terms of independent components. Most ICA methods are based on the minimization or maximization of an objective function [28-33 & 35]. This makes them exhibiting a drawback: each run yields slightly different results [33].

In this paper, a modified ICA method is employed to avoid the drawbacks for the detection of the motor faults. ICA is applied many times to extract the independent components from extended data. The most independent components are selected from all the results and kept as the global independent components to compress the measured data to the smaller data sets, which are formed by projecting the measured signal onto the directions of the most independent components [19].

The process of ICA-based feature extraction is carried out in 2 stages, namely: the identification of the most dominating independent components and the feature extraction.

B. Identification of Most Dominating Independent Components

The ICA algorithm is adopted to find all the independent components from a chosen set of measured signals. ICA extracts the independent components from the measured signals. The components are time series with the same length and unit as the measured signals. Using more signals should result in the same set of dominating independent components [19]. After performing ICA on the chosen sets of signals, the independent components are obtained as shown in Fig. 3(b). The total number of independent components is the same as the number of chosen signal sets.

Each component in Fig. 3(b) is calculated from all the chosen signals shown in Fig.3 (a). On the other hand, each chosen set of signals $x_i\left(i = 1,2,\ldots 6\right)$ can be represented as a linear combination of all the independent components [19]:

$$x_i = \sum_{j=1}^{6} A_{i,j} \cdot IC_j, i = 1,2,\ldots,6 \tag{5}$$

IC_j is the j^{th} independent component that has a size of 1×50100, where j runs from 1 to the number of independent components.

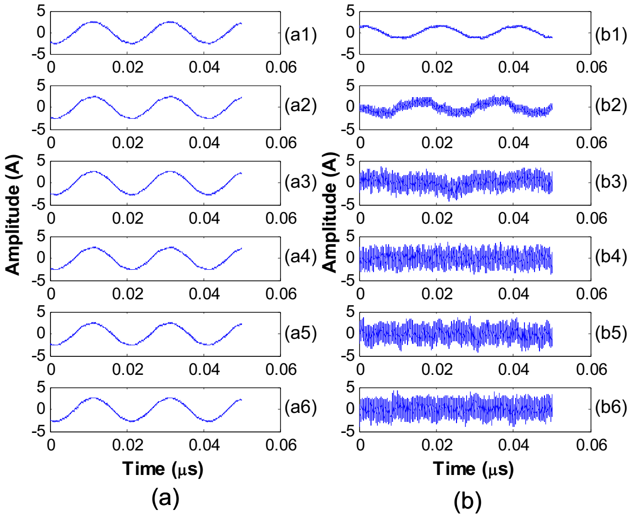

Fig.3. Typical Signals and Independent Components

(a1)- (a2): Healthy; (a3)-(a4): Bearing; (a5)-(a6): Broken Rotor Bar
(b1)- (b6): Independent Components

C. Feature Extraction of Stator current Signals by ICA

Each set of selected signals as in Fig. 3 (a) has a length of 50100 elements. It is highly desirable to compress the measured set to a smaller working set in order to improve the efficiency of on line classification without sacrificing much of the discriminating power of the original signals [19]. In order to reduce the complexity of the involved problem, two most dominating independent components are being identified with the calculation of the projection variance. The variance of the projections onto the p^{th} independent component is defined as [19]:

$$Var_p = \frac{1}{5}\sum_{i=1}^{6}\left(a_{i,p} - u_p\right)^2 \qquad (6)$$

where $a_{i,p}$ is the projection of i^{th} signal set on the direction of p^{th} component, u_p is the mean of the vector$[a_{1,p}, a_{2,p}, \ldots, a_{6,p}]$. As a result, only two independent components with the biggest variance are selected as the most dominating independent components.

All the measured signals, which describe three types of motor conditions, are compressed into a smaller working data by projecting them onto the two most dominating independent components by the equation [19]:

$$ICF_{m,n} = Signal_m \bullet ICA_n^T \qquad (7)$$

where $m = 1,2,\ldots,N; n = 1,2$; $ICF_{m,n}$ are the independent component features of the signals. $Signal_m$ is the m^{th} measured signal and ICA_n^T is the most dominating independent component.

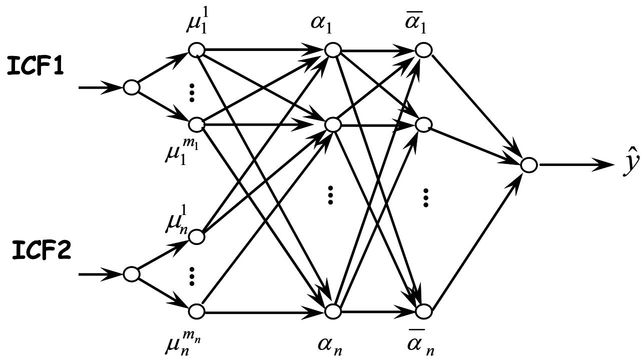

Fig. 4 FNN Structure

IV. HEALTHY & FAULTY PATTERN CLASSIFICATION USING FUZZY NEURAL NETWORK

The FNN aims to achieve robust and online classification of data. Independent component features are used to train and to test the FNN for classifying between the healthy & faulty patterns.

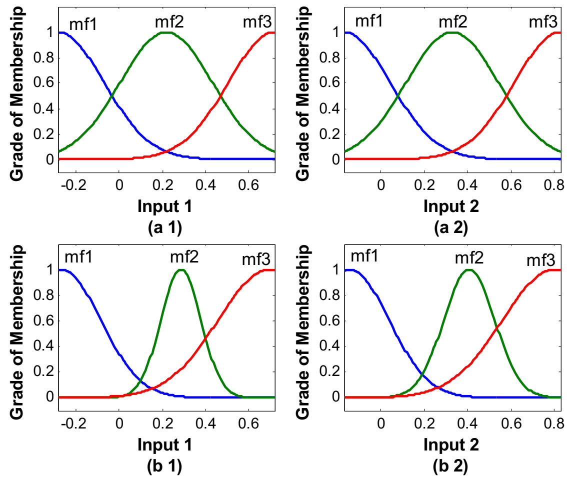

Fig. 5 FNN Membership Functions

FNN has been successfully used for prediction, detection and classification [20-27]. The FNN structure as shown in Fig. 4 is described in [24-26]. In this paper, the input layer of the FNN has more than two neurons if the number of input variables of the antecedent is more than two. The output layer of it has only one output neuron. The number of membership functions of every input is 3 or more than 3 as the problem became more complicated. The Gaussian membership functions are selected as input membership function in this FNN.

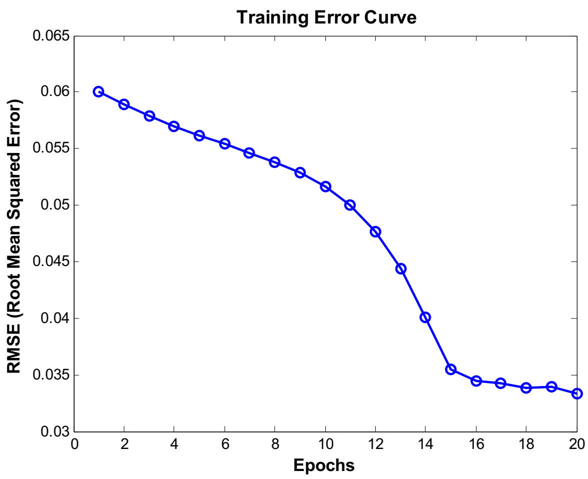

Fig.6 FNN Training Performance

Fig. 5 presents the membership functions of the FNN. Fig. 5 (a1) and (a2) represent the membership function of the two input of its initial structure. Fig. 5 (b1) and (b2) represent the membership function of two inputs of the FNN structure after being trained using the healthy and faulty patterns of motor signals. Fig. 6 illustrates the training curve of the FNN. The training usually converges in less than 20 epochs. Details about the motor fault detection will be discussed in the next sections.

V. RESULTS AND DISCUSSIONS

As shown in Table I, there are 30 sets of no-load (level 0) signals and 15 sets of signals under each other load level (1-5) to be collected from each of the healthy motor, the motor with bearing fault, and the motor with broken rotor bars. Altogether, 315 set of the data are collected.

Fault detection results based on ICA and FNN are presented and discussed. Different lengths of signal data are obtained by setting different sample rates. However, all measured signals are preprocessed and a fixed number of 50100 samples are packed in each data set for analysis by ICA & FNN for a common basis of comparisons.

TABLE I. DATA USED IN STUDY

Motor	Load level	Number of the signals
Healthy	0	30
	1	15
	2	15
	3	15
	4	15
	5	15
Bearing fault	0	30
	1	15
	2	15
	3	15
	4	15
	5	15
Broken rotor bars	0	30
	1	15
	2	15
	3	15
	4	15
	5	15

(A) Health & Fault Signatures Generated by ICA

Figs. 3(a1)-(a2), 3(a3)-(a4) & 3(a5)-(a6) each shows two typical signals measured from the three motors. It is difficult to use visual examination for detecting the respective motor fault from these signals. In contrast, the task would be much easier by visually examining the waveforms of the most dominating independent components, as shown in Figs. 3(b1)-(b2), 3(b3)-(b4) & 3(b5)-(b6), as these waveforms have now contained the most essential information about the health or fault signature of each motor.

Using Eqn. 7, these waveforms are each compressed into a feature which also preserves the essential information about the healthy or fault signature of each motor as shown in Figs. 7 & 8. Only the two most dominating independent components are sufficient for representing the health or fault signature of each motor. Great dimensional reduction is thus achieved, as only 630 (=2 features per data set x 315 data sets) features are needed to represent all the health or fault signatures. As shown in Figs. 7 & 9, the fault detection is reliable and robust under all six load levels of the motors. The ICA is thus seen to be an ideal candidate for detecting faults on motors running with changing loads.

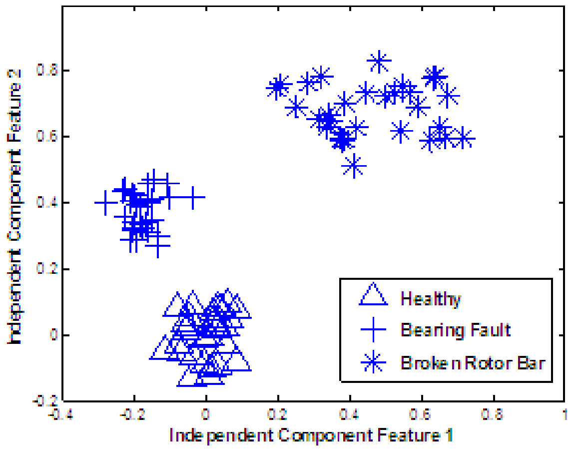

Fig. 7 No-load Healthy & Faulty Signatures

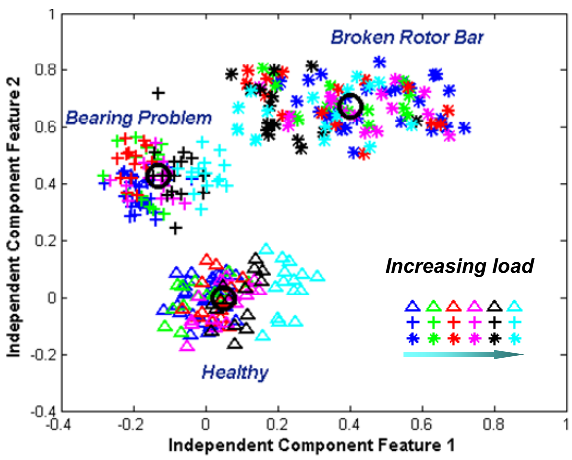

Fig. 8 On-load Healthy & Faulty Signatures

(B) Fault Classification by FNN

The FNN is trained using 1/3 of the 90×2 features of the three motors under no-load. Training converges in less than 20 epochs. As illustrated in Fig. 9, the number of misclassified patterns in the test is zero. The FNN is then trained using 1/3 of all the 315×2 features extracted from all three motors running under all six load levels. The training converges in 20 epochs. As shown in Fig. 10, there are 2 misclassified patterns. After increasing the number of membership functions of every input to 5, the number of misclassified patterns is zero as shown in Fig. 11.

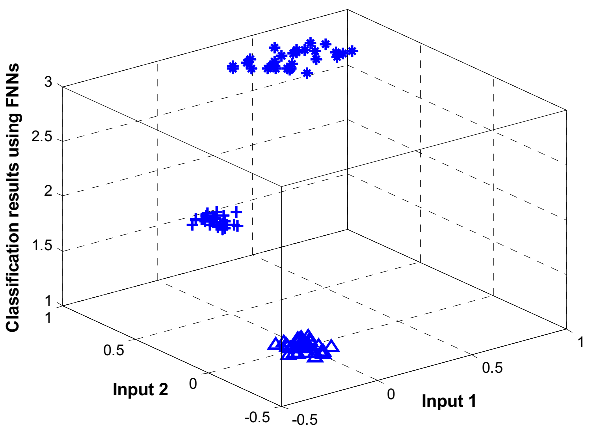

Fig. 9 No-load FNN Classification

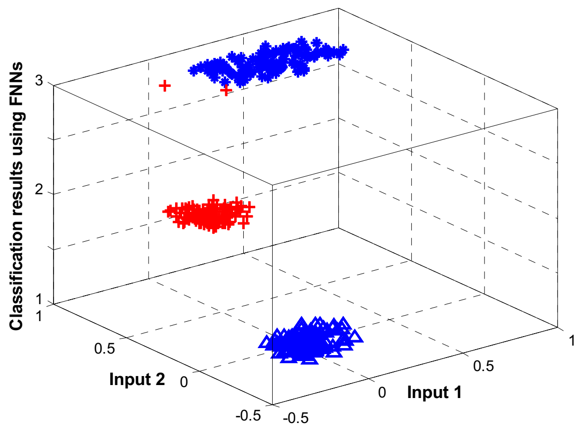

Fig. 10 On-load FNN Classification with 3 Membership Functions for Each Input.

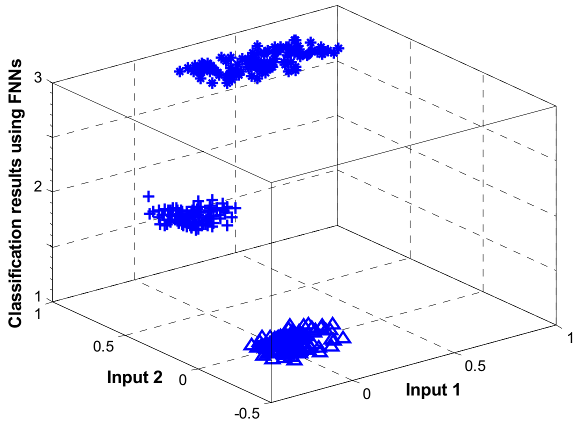

Fig. 11 On-load Classification with 5 Membership Functions for Each Input

Table II shows the improved classification accuracies with other increased numbers of membership functions in its two inputs. The observation is consistent with those made in our previous paper and other literature.

TABLE II CLASSIFICATION WITH DIFFERENT NUMBER OF MEMBERSHIP FUNCTIONS IN ITS INPUTS

The number of the membership functions about the two inputs	Training convergence time(s) at the 20th epoch	Number of the misclassified patterns on the test
2, 2	0.04	2/315
3, 3	0.09	2/315
4, 4	0.19	1/315
5, 5	0.37	0/315
6, 6	0.67	0/315

VI. CONCLUSIONS

A new scheme for online fault detection of induction motor is presented. This scheme utilizes ICA to extract the signatures of the stator currents under different loads and FNN to classify motor faults in on-line environment. Signals taken from the stator currents are analyzed by an improved ICA and the most dominating independent components are extracted over an extended data set. After training, the FNN is demonstrated to provide robust, fast, flexible and reliable fault detection on induction motors under varying load conditions, which is suited for online applications.

Our work is being extended to induction motors being fed from inverters, which supply noise-corrupted voltages at variable frequencies. Our initial results are promising, and details about this phase of work will be reported soon.

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