SOBI-ANN Based Induction Motor Fault Classification

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***Abstract*—The Induction motor fault can lead to financial loss in any place where it is used. Hence, an early detection and diagnosis of fault and its classification becomes most important for the smooth working of the system. In this paper the study proposes an algorithm for fault classification. The second order blind identification method (SOBI) is used for calculating the estimates and these estimates are given to the ANN for fault classification. Result indicates the input requirements are reduced for the classification of faults when 14 statistical parameters of 2^{nd} and 3^{rd} estimates of SOBI are given to the ANN.**

***Index Terms*—SOBI, BSS, ANN, Fault Classification**

I. Introduction

The induction motor ranks among the most frequently employed motors within industrial settings. About 60% of the industrial load is induction motor load. The induction motor fault causes the industrial process to halt. This causes huge amount economic losses to the industries. The types of fault those an induction motor come across are rotor faults and stator faults. The rotor fault accounts for 20% faults on the induction motor. Rotor faults encompass categories such as rotor eccentricity, damage, fracture or deformation of rotor cage bars, and cracks or fractures in end rings, as well as rotor bowing [1]. The total faults of induction motor 40% faults reported are the bearing fault. Stator related issues generally be divided into two main groups: (i) faults related to laminations and the frame and (ii) faults associated with stator windings. These faults can occur in an induction motor due to various stress factors, including mechanical, thermal, electrical, and environmental factors, leading to potential fault conditions[2].

Numerous techniques and technologies are being suggested for identifying fault conditions in various systems. These methods include Employing electromagnetic field monitoring via coils wound around motor shafts particularly in context of axial flux detection and utilizing search coils, Utilizing infrared recognition, Monitoring radio-frequency and (RF) emissions, Assessing noise and vibration, Measuring acoustic noise, Implementing motor-current signature analysis (MCSA), Employing model-based, artificial intelligence based, and neural network-based approaches. Various techniques have been suggested for fault detection and classification, including methods such as MCSA, Park's Transform, Artificial Neural Networks,Finite Element Method, Concordia Transform, Vibration Testing and Analysis, Multiple Reference Frames Theory, External Magnetic Field Analysis, Power Decomposition Technique,KU Transformation Theory and Wavelet Analysis. Among all the methods the MCSA, ANN and Wavelet Analysis method has been widely used because of the several advantages. For rotor faults detection and classification various methods have been used like Fast Fourier Transform (FFT), Short Time Fourier Transform (STFT), Discrete Wavelet Transform (DWT), finite element analysis, Vienna Monitoring Method, and wavelet transform based methods[3]. For stator faults mostly discussed and occurred fault is a bearing fault, then interturn faults are considered. To detect and classify bearing and interturn fault various methods for detection and classification have been proposed the negative and zero sequence currents for detection, checking for the additional air gap flux harmonics, instantaneous power signatures, random forest classifier, Park's Transform, Principal Component Analaysis(PCA), Artificial Neural Network (ANN), Fuzzy classifier are used [2][3].

In addition to these approaches, researchers have delved into a novel realm of fault detection and classification known as blind source separation (BSS) methods. There are several algorithms in BSS like information maximization algorithm, Fixed point algorithms(ICA), JADE algorithm[4]. ICA uses the higher order statistical properties to linearly mixed signals into independent components, all without any prior information about original components or mixing process[5]. The ICA method is used over the FFT output and its standard deviation in region of interest were found to be fault discriminant [6]. The ICA method along with some constrained is used to classify the fault. The information is contained by the signals in terms of independent component is less so the c-ICA algorithms can classify the fault based only if prior knowledge of mechanical information is known as reference[7]. The ICA technique is employed to identify faults in induction motor by determining a threshold and triggering a fault detection if any condition surpasses this condition[8]. Form above results we come to the conclusion that ICA can be used for the fault detection but will not be suitable for the fault classification. So another method and area of BSS algorithms is higher order statistics (HOS) called as Second Order Blind Identification method (SOBI). This paper is organized in eight chapters. The second chapter will explain about the SOBI method its advantages and disadvantages. Third chapter presents introduction to Artificial Intelligence. Fourth chapter presents feature extration. Fifth chapter will present the algorithm for classification of the faults of induction motor. Sixth chapter will discuss the experimental setup and observations. Seventh chapter will present the results and discussions. Eight chapter will present the conclusion and future scope.

II. Second Order Blind Identification (SOBI) Method

The method was introduced by Belouchrani et al., in 1997 [9]. Second-Order Blind Identification (SOBI as introduced by Belouchrani et al. in 1997), leverages the temporal interdependencies of components through the joint diagonalization of one or multiple auto-covariance matrices. After that several authors have used this algorithm for source separation and finding out the valuable information for detection and classification in various area of application. The SOBI method has found application in various domains, including artifact removal from EEG data [9], the identification of significant signals in brain EEG data [10], the separation of vibrations originating from underground traffic, and the prediction of wind speed. SOBI has gained recognition as a well-established and extensively researched technique for separating uncorrelated weakly stationary time series. For different time series and BSS model this method has to be provided with some modification [11]. The SOBI method has been successfully implemented by the Oliveira et al. in 2020 for harmonic and inter harmonic classification of Power Quality disturbances. Applying the same concept here the induction motor fault classification is achieved [12]. The SOBI algorithm operates by approximating the joint diagonalization of two correlation matrices characterized by different delays. When *z[n]* a whitened vector is provided, it investigates for a collection of *r* delayed correlation matrices for *z[n]*, denoted as $R_z(\tau_i)$ for *i* = *1,...,r*. The objective of SOBI is to find a unitary transformation V such that:

$$V^T R_z(\tau_i) V = D_i fori = 1, ..., r \tag{1}$$

where, D_i refers to a collection of covariance related to the estimated signal *y[n]*.By working with several correlation matrices, SOBI reduces the probabilities of incorrect delay selection interfering with blind separation process. Put simply, the steps to execute the SOBI can be summarized as follows:

1.Evaluate the MxM correlation matrix $R_x(0)$ of signals *x[n]* as:

$$R_x(0) = E[x(0)x^T(0)] = \frac{1}{N - M + 1} X X^T \tag{2}$$

where X is called as the Hankel matrix

2.Estimate the EVD of $R_x(0)$:

$$R_x(0) = V_x D_X V_x^T \tag{3}$$

where $V = [v_1, v_2, \ldots\ldots, v_M]$ is an MxM unitary matrix having eigenvectors of $R_x(0)$ and D_x is an MxM diagonal matrix having eigenvalues $\lambda_1, \lambda_2, \lambda_3, \ldots, \lambda_M$ of $R_x(0)$ prepared in descending order.

3. A white vector *z[n]* is obtained by performing whitening of *x[n]* through the whitening matrix Q,

$$z[n] = Q_x[n] \tag{4}$$

Where,

$$Q = D_x^{(-(1/2))} V_x^T \tag{5}$$

4. Calculate H delayed sample correlation matrices $R_z(\tau)$ from *z[n]* for a set of fixed delays

$$\tau\epsilon(\tau_j j = 1, \ldots.., H); \tag{6}$$

5.Obtain the unitary matrix V , which is the joint diagonalizer of the set of correlation matrices $(R_z(\tau_j), j = 1, \ldots, H)$, by applying the Givens Rotation method[12];

6.Estimate the output signals as:

$$y[n] = V^T Q_x[n] \tag{7}$$

And or the mixture matrix A, as A=Q*V.

Where * denotes the Moore-Penrose pseudo-inverse.

Experimental findings have indicated that employing multiple correlation matrices is more effective and resilient in scenarios characterized by low signal-to-noise ratio (SNR) and/or sources with minimal spectral distinctions[12].

III. ARTIFICIAL INTELLIGENCE

Neural network is recognized as a biologically inspired computational method. It consists of the processing element, connections, and coefficients. The processing elements are neurons, connections are training and recall algorithms and coefficients are the weights given to connections.The Architecture of Artificial Neural Network is shown in *Figure*1. Artificial neural networks possess key attributes such as adaptability in learning, the ability to generalize, parallel processing at scale, resilience, the capacity for associative information storage, and processing of spatiotemporal information [13]. Artificial intelligence is being used in various area of applications like pattern recognition, speech recognition, biomedical

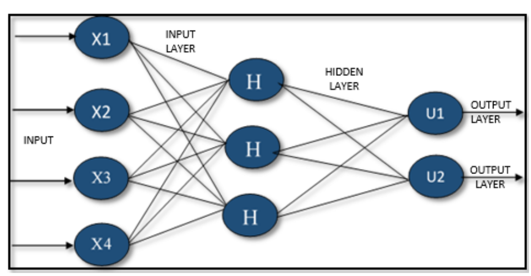

Fig. 1. Architecture of Artificial Neural Network

diagnosis applications, induction motor fault detection and diagnosis, and many more[14]. The neural network illustrated here is organized in three tiers: an output layer, a hidden layer and an input layer . The artificial feed-forward network topology is selected for simplicity. The choice for training input patterns involves utilizing a feedforward network, while error computation and weight adjustment based on error calculations are accomplished through backpropagation. The progression goes from input layer to hidden layer and to the output layer.

IV. FEATURE EXTRACTION

It is necessary to develop a feature extraction approach for classifying defects. Statistical parameters are extracted to classify the different faults. These statistical parameters include minimum, maximum,variance, avegare(mean), middle value(median), addition(sum), absolute addition(sum), shape factor, root mean square value(RMS value), kurtosis, energy, crest factor, standard deviation and skewness of captured stator current signals. The mathematical formula and its calculations can be referred in detail in [15].

V. PROPOSED ALGORITHM

Step1: Capture three phase current of the Induction motor for processing.

Step2: Take transpose if captured signal is in column and apply SOBI Algorithm to the signal

Step3: Calculate 14 statistical parameter of 2^{nd} and 3^{rd} estimate

Step4: Apply ANN classifier for the classification of the faults and obtain confusion matrix and the ANN classifier model

VI. EXPERIMENTAL SETUP AND OBSERVATIONS

For the purpose of experimentation and data generation, a squirrel cage induction motor with the following specifications is employed: 2 H.P, 3-phase, 4 poles, 415 volts, 50 Hz. The experimental set up is shown in *Figure* 2.

This motor has 24 coils distributed across 36 slots. Each phase consists of 8 coils, each comprising 300 turns. A tapping configuration is applied to each phase, with the tapping starting at 10 turns from the neutral point. With each group containing approximately 70 to 80 turns, tapping are drawn from these coils. To capture the current and voltage signals, an ADLINK DAQ system is used, operating at a sampling frequency of

Fig. 2. Experimental Setup

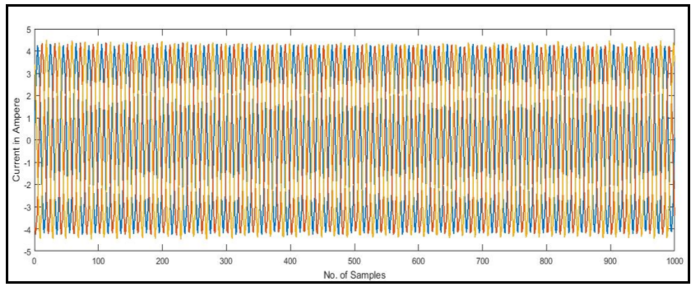

Fig. 3. 3-phase Current signal of the healthy condition of induction motor

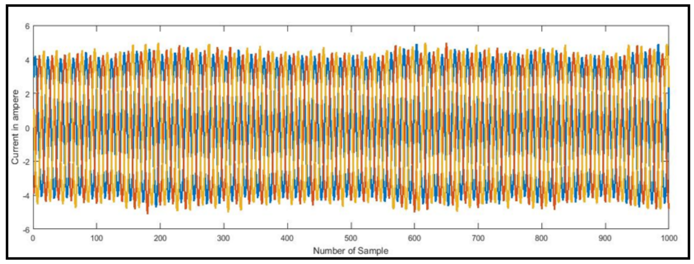

Fig. 4. 3-phase Current signal of the bearing fault of induction motor

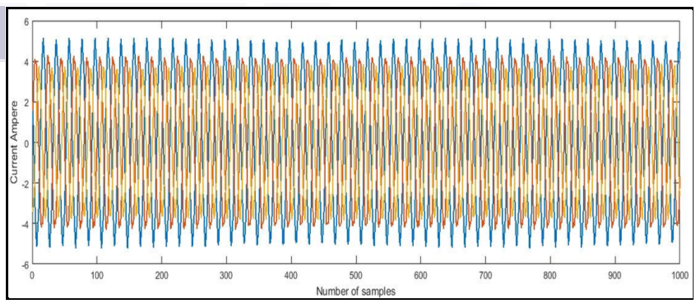

Fig. 5. 3-phase Current signals of inter turn fault of Induction motor

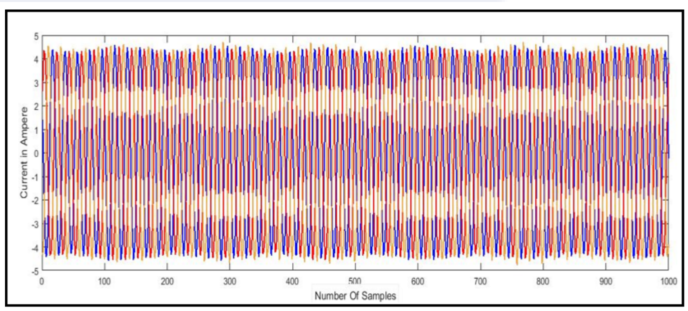

Fig. 6. 3-phase Current signal of rotor bar crack of Induction motor

1 kHz, and data is collected under various load and supply conditions for the specific cases outlined in *Figure* 3 to *Figure* 6. The *Figure* 3 to *Figure* 6 display the 3-phase current signals corresponding to different fault conditions in the 3-phase induction motor.

The various condition of fault current are processed through the SOBI algorithm then 3 estimates are obtained. Note that the 3^{rd} estimate and 2^{nd} estimate shows the largest variations

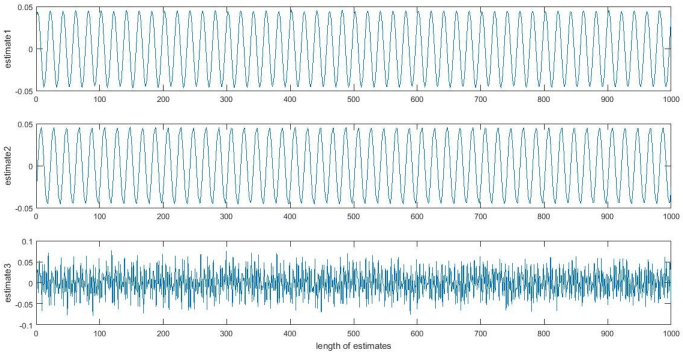

Fig. 7. SOBI demixing matrix estimates for healthy condition

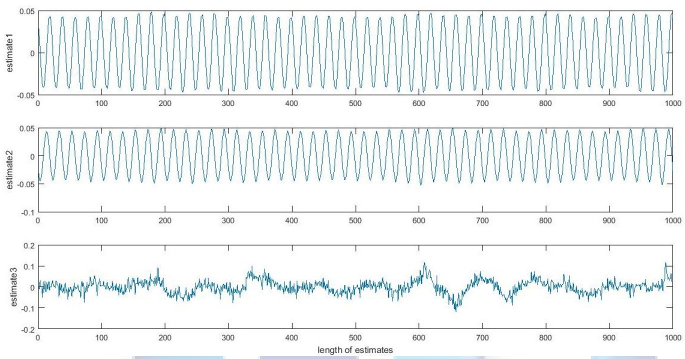

Fig. 8. SOBI demixing matrix estimates for bearing fault condition

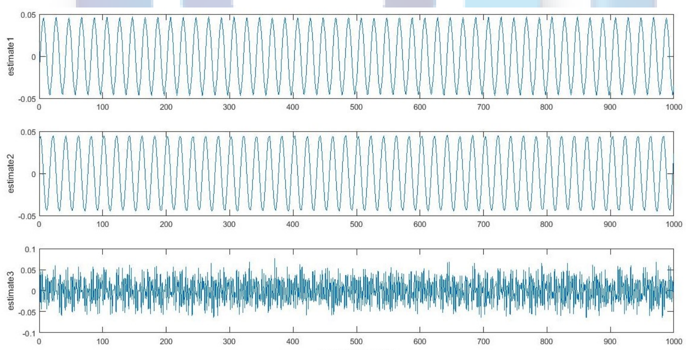

Fig. 9. SOBI demixing matrix estimates for Interturn Fault Condition

when compared with the healthy conditions and fault condition. The SOBI decompositions are as shown in *Figure*7 to *Figure*10 for various fault condition when motor is on load. Form observation of *Figure*7 to *Figure*10 it is clearly visible that 3^{rd} and 2^{nd} estimates of faulty condition demonstrate the significant variation as compared to the healthy condition. Hence 14 statistical parameter has been calculated for both of the estimates. These 14 statistical parameters of 3^{rd} and $2^{n}d$ become the input to the ANN.

VII. Results and Discussion

It is clearly seen that 3^{rd} and 2^{nd} estimate of the SOBI demixing matrix shows greater variations, so statistical parameter of 3^{rd} and 2^{nd} estimate has to be calculated. The total 10

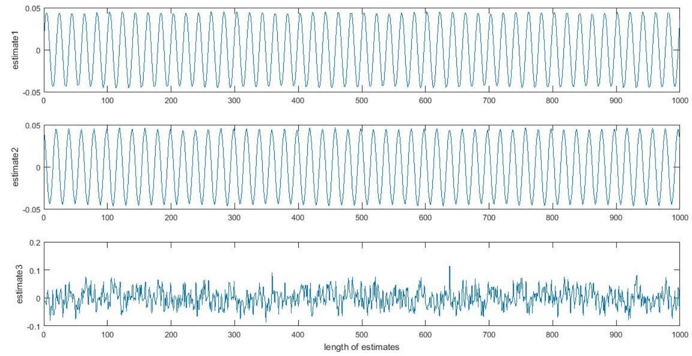

Fig. 10. SOBI demixing matrix estimates for Rotor-bar fault condition

reading are taken for each fault, hence 28x40 matrix of statistical parameters is obtain. An artificial neural network (ANN) with its strong pattern recognition abilities proves to be a valuable tool for the classification of faults in induction motors. This study utilizes a three-layer Feed Forward ANN (FFANN) trained through a supervised learning technique known as Back Propagation. The FFANN structure contains an input layer, hidden layer, and an output layer. The input layer comprises 28 nodes corresponding to statistical features derived from the 3^{rd} and 2^{nd} estimates of the SOBI demixing matrix, 12 neurons in the hidden layer. Meanwhile, the output layer is represented by four processing elements, each representing one of the following conditions: rotor bar crack, interturn fault, bearing fault and healthy condition.The ANN model obtained after training is shown in *Figure 11*. Randomized data is given as input into the network, to ensure generalization and the Transigmoid transfer function is employed for training purposes. This training process yields a percentage accuracy for classification. Considering these foundational principles, the research investigates the relationship between the accuracy percentage in categorizing induction motor states and the quantity of processing elements within the hidden layer. It can be clearly observed that the ANN is able to classify the faults with 100% accuracy considering the healthy condition. The

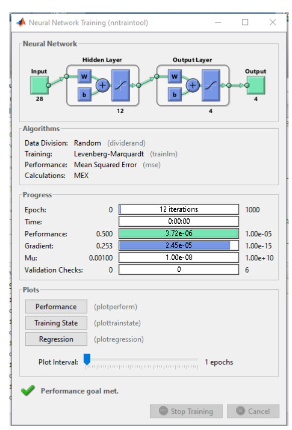

Fig. 11. ANN Training Model for induction motor fault classification

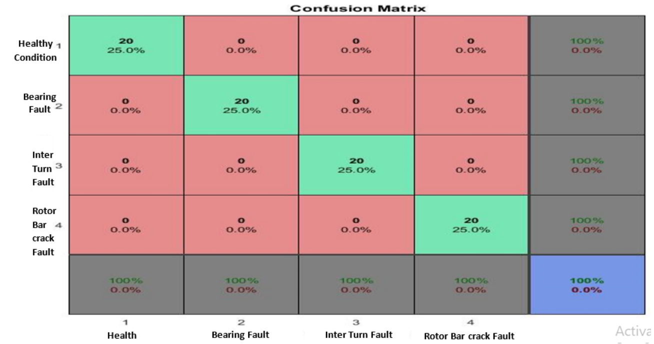

Fig. 12. Confusion Matrix for classification of induction motor fault

TABLE I
COMPARISON OF THE VARIOUS PARAMETERS OF ANN AND SOBI ESTIMATES AND CLASSIFICATION RESULTS

Estimate No. selected for the statistical calculation and feed to ANN	Neuron Input	Neuron output	No. of hidden layers	No. of hidden Neurons	Confusion matrix classification
All 3 estimate	42	4	1	7	100%
Only 3rd estimate	14	4	1	11	98%
2nd and 3rd estimate	28	4	1	12	100%

confusion matrix obtained after training is shown in *Figure 12*. Table 1 displays the accuracy of classification when all the statistical features from the estimates are input to the ANN, resulting in a 100% classification accuracy rate. So as to check whether ANN can classify all the conditions with less number of input only the statistical parameter. The classification accuracy when the statistical parameter of only 3^{rd} estimate is considered then only 98% classification accuracy is obtained. Hence to improve classification accuracy 2^{nd} estimate along with 3^{rd} is considered for processing and 100% classification accuracy is obtained here.

VIII. CONCLUSION AND FUTURE SCOPE

The paper proposes SOBI-ANN based induction motor fault classification. SOBI algorithm is used as signal separation method to identify the dominant fault signals and is given to the ANN after feature extraction for classification as ANN has good classifier properties. As this method is a time domain based method its computational complexity is less and time required to perform classification also reduced. Now this work could be extended by applying dimension reduction methods to select the dominant features after calculating the statistical parameter those are feed to ANN for classification.

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