Paper accepted for presentation at 2009 IEEE Bucharest Power Tech Conference, June 28th - July 2nd, Bucharest, Romania

Fault Detection in Induction Motors with Independent Component Analysis (ICA)

Irfan Guney, Erdal Kilic, Okan Ozgonenel, Mustafa Ulutas, Erol Karadeniz

Abstract – **In this study, the aim is to detect an induction motor's winding faults by using independent component analysis (ICA). Many laboratory experiments have been done on an induction motor to check the performance of the proposed method. The phase currents of the induction motor are used in the fault detection algorithm. The algorithm is implemented by using MATLAB. The proposed method is compared to FFT solution to see its ability to distinguish fault currents. It has been observed that the proposed method based on ICA can efficiently be used to detect induction motors winding faults.**

Index Terms – **Internal Fault, ICA, FFT, stator faults**

I. INTRODUCTION

Nowadays, induction motors are widely used in industry due to their low cost and mechanical stability. They former the critical components of the production processes. Faults cause time and product losses to the production processes. If the faults can not be determined in the complex systems their early stage, they may cause much money and man losses. Turn faults in the stator winding of an induction machine leads to an asymmetry between the three phases, causing undesirable motor behavior. This insulation breakdown in the stator winding corresponds to nearly 40% of the total motor failures. [1].

Generally speaking, there are three types of fault in the induction motors: stator, rotor and bearing fault. Any fault in the rotor causes high temperature, vibration and torque changes in the motor. Mechanical fault detection methods are needed to determine rotor faults. These methods are based on detecting and analyzing of the rotor and stator currents [2], [3]. The main problem in the three phase induction motors is to detect incipient faults [4], [5]. Hence, incipient fault detection and diagnosis (FDD) problem have been investigated in literature more.

In this study, the main aim is to detect induction motor faults in real time to use motor current information. This method can also be called current signal processing (CSP). CSP is also used to detect broken bar faults and non-uniform air gap faults [7]. CSP methods are generally based on fast Fourier transform (FFT). Lately, Wavelet based methods are used to solve FDD problems [6], [8].

Principal component analysis (PCA) and ICA used to solve FDD problems is called statistical method. These methods can be used to solve FDD problems in real time to lessen the data length. In literature, one can see several different implementations of the PCA and ICA [9], [10], [11].

II. APPLYING ICA to FAULT DETECTION ALGORITHM

2.1 ICA Background

ICA decomposes mixed input data into a set of independent components (ICs) without any information about the distribution of the sources, i.e. blind separation of sources. Whereas Principal Component Analysis (PCA) uses second order spatiotemporal correlation information for data decomposition, ICA uses higher-order statistics.

ICA can simply be defined by using a statistical "latent variables" model. Assume that we observe n linear mixtures $x_1,..., x_n$ of n independent components

$$x_j = a_{j1}s_1 + a_{j2}s_2 + ... + a_{jn}s_n \text{ for all } j. \tag{1}$$

We assume that each mixture x_j as well as each independent component s_k is a random variable, instead of a proper time signal. The observed values $x_j(t)$, e.g., the microphone signals in the cocktail party problem, are then a sample of this random variable. Without loss of generality, we can assume that both the mixture variables and the independent components have zero mean: If this is not true, then the observable variables x_i can always be centered by subtracting the sample mean, which makes the model zero-mean. It is convenient to use vector-matrix notation instead of the sums like in the previous equation. Let us denote by **x** the random vector whose elements are the mixtures $x_1,..., x_n$ and likewise by **s** the random vector with elements $s_1,..., s_n$. Let us denote by **A** the matrix with elements a_{ij}. Generally, bold lower case letters indicate vectors and bold upper-case letters denote matrices. All vectors are understood as column vectors; thus x^T, or the transpose of **x**, is a row vector. Using this vector-matrix notation, the above mixing model is written as

$$x = As. \tag{2}$$

Sometimes we need the columns of matrix **A**; denoting them by a_j the model can also be written as

$$x = \sum_{i=1}^{n} a_i s_i . \tag{3}$$

---

[1] I. Guney, Acibadem University, Altunizade Mahallesi Fahrettin Kerim Gökay Caddesi, No:49, Üsküdar, 34662, Istanbul, TURKEY (e-mail: irfan.guney@acibadem.edu.tr).
[2] E. Kilic is with Ondokuz Mayis University, Computer Engineering Department, Kurupelit – 55139 – Samsun – TURKEY (e-mail: ekilic@omu.edu.tr).
[3] O. Ozgonenel (Member IEEE) is with Ondokuz Mayis University, Electrical & Electronic Engineering Department, Kurupelit – 55139 – Samsun – TURKEY (e-mail: okanoz@omu.edu.tr).
[4] M. Ulutas (Member IEEE) is with Ondokuz Mayis University, Computer Engineering Department, Kurupelit– 55139 – Samsun – TURKEY (e-mail: ulutas@ieee.org)
[5] E. Karadeniz is with Ondokuz Mayis University, Electrical & Electronic Engineering Department, Kurupelit– 55139 – Samsun – TURKEY (e-mail: ekaradeniz@omu.edu.tr).

The statistical model in Eq. 2 is called independent component analysis, or ICA model. The ICA model is a generative model, which means that it describes how the observed data are generated by a process of mixing the components s_i. The independent components are latent variables, meaning that they cannot be directly observed. Also the mixing matrix is assumed to be unknown. All we observe is the random vector **x**, and we must estimate both **A** and **s** using it. This must be done under as general assumptions as possible.

The starting point for ICA is the very simple assumption that the components s_i are statistically *independent*. We must also assume that the independent component must have *nongaussian* distributions. However, in the basic model we do *not* assume these distributions known (if they are known, the problem is considerably simplified.) For simplicity, we are also assuming that the unknown mixing matrix is square. Then, after estimating the matrix **A**, we can compute its inverse, say **W**, and obtain the independent component simply by:

$$s = Wx \tag{4}$$

ICA is very closely related to the method called *blind source separation* (BSS) or blind signal separation. A "source" means here an original signal, i.e. independent component, like the speaker in a cocktail party problem. "Blind" means that we no very little, if anything, on the mixing matrix, and make little assumptions on the source signals. ICA is one method, perhaps the most widely used, for performing blind source separation. In many applications, it would be more realistic to assume that there is some noise in the measurements, which would mean adding a noise term in the model. For simplicity, we omit any noise terms, since the estimation of the noise-free model is difficult enough in itself, and seems to be sufficient for many applications [14], [15].

In literature, several different implementations of ICA can be seen. For example, Fast ICA is an efficient method to estimate ICs in time series. It is observed that, this method is 10-100 times faster than the other methods that are used to reduce data dimension [12], [13].

2.2 Fault Detection with ICA

In this study, ICs that are obtained with fast ICA have been used in the fault algorithm to detect induction motors incipient faults. The fault detection algorithm proposed based on ICA is as:

1. Obtain **s** (i.e., ICs) and **A** matrices by using Eq. 2 and **x** matrix that is constructed by using motor current when the motor woks healthy condition.
2. Calculate **W** matrix by utilizing the relationship between **W** and **A** matrices as $W = A^{-1}$.
3. Estimate s_E by using **W** matrix and x_m matrix that is a measurement matrix constructed by using motor current when the motor woks real time.
4. Calculate residual with Euclidian norm as: $$R = \|s - s_E\|^2 = \|Wx - Wx_m\|^2 \tag{5}$$
5. Determine a threshold value to decide fault. If the calculated residual exceeds this value, which means that any incipient faults occurs in the motors.

III. EXPERIMENTAL STUDIES

A custom-built 1 kVA, four poles, 50 Hz asynchronous motor is used for laboratory experiments. Different tap windings are extracted to perform internal fault studies. A number of internal fault are performed to the see accuracy of the proposed fault detection system. Fig. 1 shows the real time laboratory experiments.

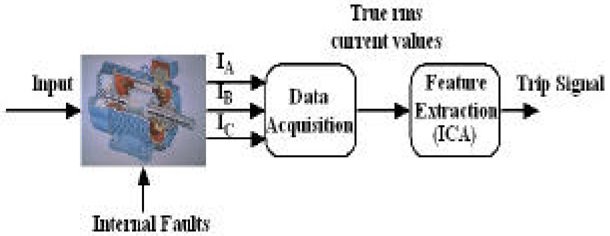

Figure 1. Laboratory test pad

A fault switch and an electromechanical relay are used for creating internal faults in stator windings. The fault time instant is selected arbitrarily. A fault resistance of 1.5Ω is used for limiting the circulating current between the turns. Each phase of the induction motor has tap windings between the turns 20-40-60 and 80. This resistance is connected in series to the short-circuited turns. True rms values of the stator currents are form in 80x3 matrix type and used for ICA computation. The sampling frequency is set to 4000 Hz which yields to 80 samples for a period. It is observed that 80 samples are quite enough for ICA computation to detect stator winding faults.

Real-time current samples are then acquired and recorded by using data acquisition card (NI-DAQ PCI 16MIO-E). Matlab ™ is used for required calculations.

Fig. 2 shows the acquired instantaneous three phase currents and calculated true rms values for phase A, B and C during normal condition.

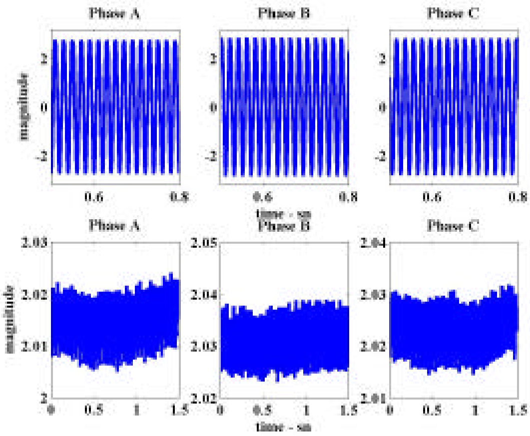

Figure 2. Instantaneous and rms stator currents during normal conditions

The first row the instantaneous stator currents while the second row shows the calculated true rms values during no-fault condition. Fig. 3 shows the calculated ICA components during normal condition. To make it clear visually, only one period data is drawn in Fig. 3.

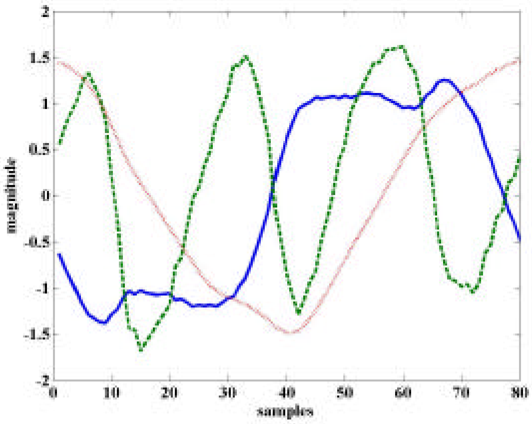

Figure 3. The calculated ICA components of the stator currents during normal condition

Fig. 4 shows the phase currents and calculated true rms values during an internal fault in Phase A winding between the turns 60 – 80. The fault is created between the 0.66 sec. and 0.76 sec.

Similarly, Fig. 5 shows the calculated ICA components for this particular internal fault study. The error vector is calculated by using Eq. 4.

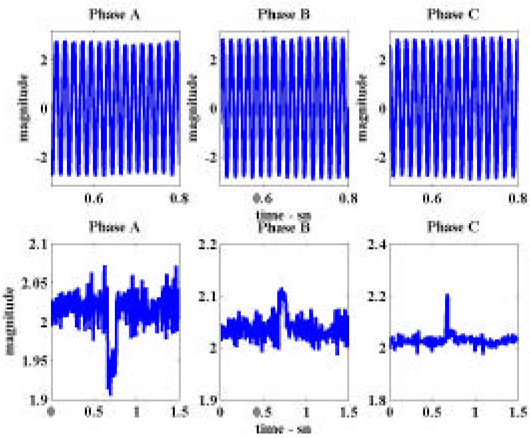

Figure 4. An internal fault condition in Phase A

Since a fault resistance of 1.5 Ω is used for limiting the short-circuited current, this is also assumed as high impedance fault. As seen in Fig. 4 the phase currents do not change significantly and it is hard to decide whether there is an internal fault.

The following Fig. 5 and Fig. 6 show the calculated error vector during normal condition and faulty condition. As seen clearly from Fig. 5 and Fig. 6 the magnitude of the error vector during internal fault condition is much bigger than it during no fault condition. A pre-specified threshold value is defined to distinguish fault currents.

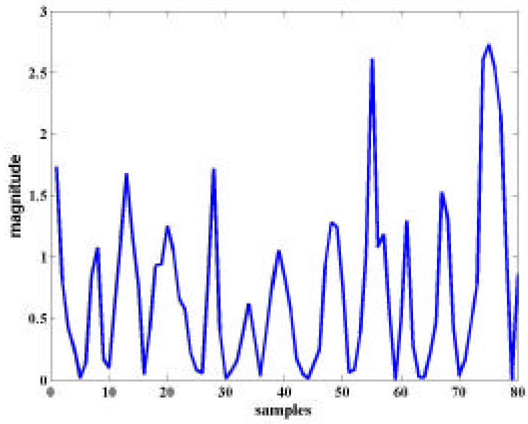

Figure 5. The calculated error vector under normal condition

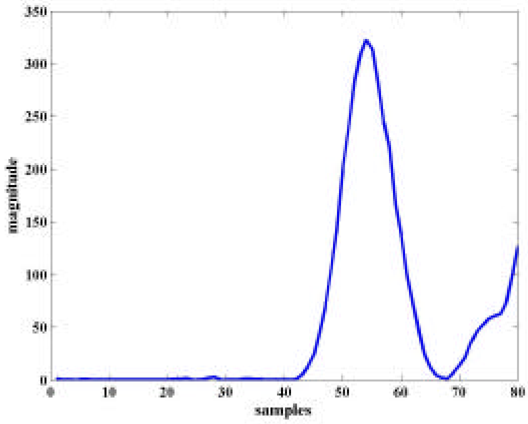

Figure 6. The calculated error vector during an internal fault in Phase A

It is clearly seen in Fig. 6 that the proposed algorithm is able to detect the fault current in a half period.

The classical approach used in the industrial environment for the detection of broken rotor bars, bearing faults or turn faults in induction machines is based on the analysis of the stator currents in steady state using harmonic components. In this work, the proposed fault detection algorithm is compared to FFT to see its performance to distinguish fault currents. The following Fig. 7 shows the rms values of the stator currents and harmonic components of the Phase A current. Harmonic components consist of the ratio of DC / first, second / first, third / first and fifth / first components. Similarly, Fig. 8 and Fig. 9 are obtained for Phase B and Phase C currents, respectively.

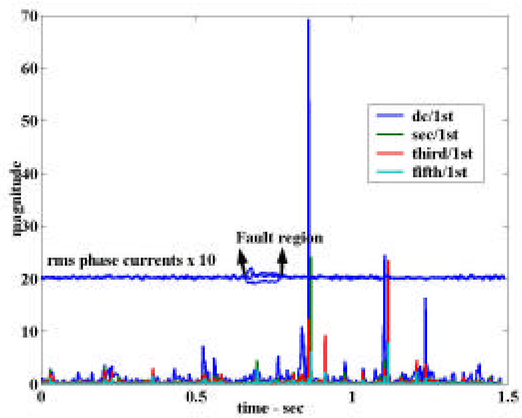

Figure 7. FFT solution for the Phase A current during an internal fault

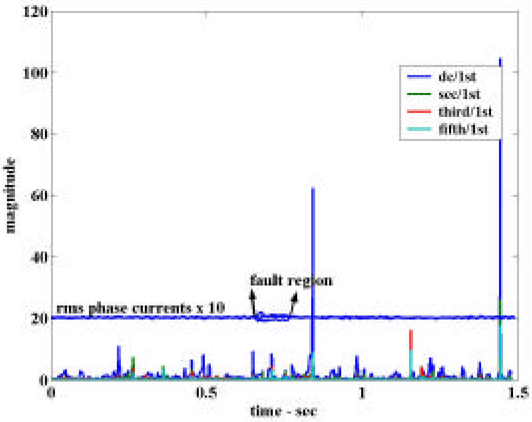

Figure 8. FFT solution for the Phase B current during an internal fault

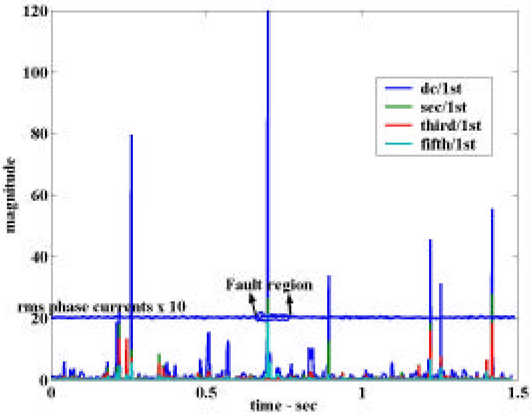

Figure 9. FFT solution for the Phase C current during an internal fault

As seen from the Fig. 7, Fig. 8, and Fig. 9 the harmonic components do not give the significant information. Even if the harmonic components occur in fault region in Fig. 9, these peaks can often occur in power system due to some transient phenomena events. However, the proposed algorithm distinguishes the fault currents from rated currents effectively as seen in Fig.6.

IV. CONCLUSION

In this study, a new fault detection method based on ICA has been proposed and implemented to detect induction motors incipient faults. Many different incipient faults are created on the three phase 1KVA induction motor to test the performance of the fault detection algorithm. It is observed that the proposed method successfully detects induction motors incipient faults. The proposed method is then compared to FFT solution to see its ability to distinguish fault currents.

As a future work, we are planning to use ICA with Neural Networks to diagnose faults correctly (i.e, to give priority and degree about fault types).

V. ACKNOWLEDGEMENTS

This work is supported by Ondokuz Mayis University under the projects MF-105 and MF-101. The authors wish to acknowledgement for these supports.

VI. REFERENCES

[1] J. F. Martins, V. Fernão Pires, and A. J. Pires, "Unsupervised Neural-Network-Based Algorithm for an On-Line Diagnosis of Three-Phase Induction Motor Stator Fault", IEEE Transactions on Industrial Electronics, Vol. 54, No. 1, February 2007.

[2] Kyusung Kim, Alexander G. Parlos, "Induction motor fault diagnosis based on neuropredictors and wavelet signal processing", IEEE/ASME Trans. On Mechatronics, Vol. 7, No. 2, June 2002.

[3] G. Didien, *et all*, "Fault detection of broken rotor bars in induction motor using a global fault index", IEEE Trans. On Industry Applications, Vol. 42, No. 1, January 2006.

[4] Masoud Haji, Hamid A. Toliyat, "Pattern recognition – a technique for induction machines rotor fault detection 'eccentricity and broken bar fault'", Industry Applications Conference, 2001. Thirty-Sixth IAS Annual Meeting. Conference Record of the 2001 IEEE Volume 3, 30 Sept.-4 Oct. 2001 Page(s):1572 – 1578.

[5] M.E.H. Benbouzid, H. Nejjari, "A simple fuzzy logic for induction motors stator condition monitoring", IEEE Transactions on Power Electronics Volume 14, Issue 1, January 1999, Page(s):14 – 22.

[6] I. Tsoumas, E. Mitronikas, A. Safacas, "Induction motor mixed diagnosis based on wavelet analysis of the current space vector", Electrical Machines and Systems, 2005. ICEMS 2005. Proceedings of the Eighth International Conference on Volume 3, 27-29 Sept. 2005 Page(s):2186 – 2191.

[7] S.H. Chetwani, M.K. Shah, M. Ramamoorty, "Online condition monitoring motors through signal processing", Electrical Machines and Systems, 2005. ICEMS 2005. Proceedings of the Eighth International Conference on Volume 3, 27-29 Sept. 2005 Page(s):2175 – 2179.

[8] Arfat Siddique, G.S. Yadava, Bhim Singh, "Identification of three phase induction motor incipient faults using neural network", IEEE Int. Symposium on Electrical Insulation, Indianapolis, USA, 19-22 September, 2004.

[9] Zang H., A. K. Tangirala, S. Shah, "Dynamic process monitoring using multiscale PCA", *Proceeding of the 1999 IEEE Canadian conference on electrical and computer engineering*, pp 1579-1584, Edmonton, Alberta, Canada May 1999.

[10] Haiging W., S. Zhihuan and L. Ping, "Improved PCA with optimized sensor locations for process monitoring and fault diagnosis", *Proceeding of teh 39th IEEE Conference on Decision and Control*, pp 4353-4358, Sydney, Australia, December, 2000.

[11] Moya E., G. I. Sainz, B. Grande, M. J. Fuente and J. R. Peran, "Neural PCA based fault diagnosis", *Proceeding of the European Control Conference*, pp 809-813, 2001.

[12] http://www.cis.hut.fi/projects/ica/fastica/ , Last access: 20/02/2007.

[13] A. Hyvärinen. 'Fast and robust fixed-point algorithms for independent component analysis" *IEEE Transactions on Neural Networks* 10(3):626-634, 1999.

[14] Sanna Pöyhönen, Pedro Jover, Heikki Hyötyniemi, "Independent component analysis of vibrations for fault diagnosis of an induction motor", Proceedings of IASTED International Conference Circuits, Signals, and Systems, May 19-21, 2003, Cancun, Mexico.

[15] G. Gele, M. Colas, C. Serviere, "Blind source separation: A tool for rotating machine monitoring by vibration analysis", *Journal of Sound and Vibration*, 248(5), 2001, page(s):865-885.