Parametric Method based Inter-Turn Incipient Short Circuit Stator Fault Detection of Induction Motor

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Abstract

Objectives: The parametric method is proposed to identify the inter-turn incipient short circuit fault of induction motor.

Methods/Statistical Analysis: The parametric methods are the high resolution methods, which are used to detect the frequencies with low signal to noise (SNR) ratio using smaller number of data samples. The subspace parametric methods use the Multi-signal Classification (MUSIC) algorithm to identify the inter-turn incipient fault and its severity. The pseudo spectrum from the MUSIC algorithm estimates the frequencies related to the faulty condition of the induction motor.

Findings: The frequencies which are related inter-turn short circuit fault are obtained from the pseudo spectrum and are compared with the estimated frequencies and thus it proves the estimated frequencies.

Application/Improvements: The proposed algorithm is used to estimate the harmonic components from the pseudo spectrum which helps to differentiate the healthy and faulty conditions of the motors. Also the severity of the fault is identified from the pseudo spectrum.

Keywords: Frequency Signal Dimension Order, Inter-Turn Incipient Short Circuit Fault, Multi Signal Classification (MUSIC) Algorithm, Parametric Method, Subspace Method

1. Introduction

Induction motors are popularly used machine in industries. Abnormalities happen in induction motor may severely affect progress of the industry. Therefore, continuous monitoring of the Induction motors are needed as it provides adequate warning of imminent failures, maintenance needs, schedules future preventive maintenance needs & repair work, minimizes the down time and optimum maintenance schedules. Condition monitoring alerts the user about the failure and it provides data for root cause and reliability analysis.

In induction motor, nearly 30 to 40% of the stator fault occurs and 21% of stator fault are estimated as the inter-turn short circuit fault. It is necessary and better to find the fault at the early stage as it may spread as severe fault in very few seconds. In our work, inter-turn incipient fault stage is considered for analysis.

One of the main classifications of fault diagnosis are non-parametric and parametric methods. Fast Fourier Transform (FFT) and its extensions are non-parametric methods. FFT gives the frequency spectrum of stator current. But, FFT results in poor accuracy, due to problems like frequency resolution, magnitude accuracy and data processing. The FFT technique is unsuitable under no load and loaded condition. Also, FFT cannot be applied for time varying currents because harmonics are not constant. Also, if the signal is buried in noise signal, fault identification becomes difficult task with FFT.

The wavelet transform based fault diagnosing methods can be used in identifying the stationary and non-stationary conditions, as they provide multi-resolution signal analysis with high resolution in time and frequency domain. But in stationary conditions, they have the disadvantage in the frequency resolution compared to subspace methods. Information Theoretical Criteria identifies the stator fault with the number of frequencies as fault index. The parametric methods are suggested for identifying the fault related frequency components present in the signal.

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To detect the low signal to noise ratio frequencies, the parametric methods are suggested. To identify the frequencies of the stator current signal, Multi-Signal Classification Algorithm is proposed. This method found to detect the frequencies of the signal which is buried in noise, with small number of data samples. The Eigen values of autocorrelation matrix calculated are separated into signal and noise subspace. MUSIC performs better compared with FFT, because it improves the frequency resolution, accuracy of the motor failure detection and reduces the noise influence.

In our work, MUSIC algorithm is applied on the stator current signal to find out the fault related frequencies in estimating the inter-turn incipient short circuit stator fault.

2. Basic Concepts

The basic concept of the proposed technique is given in this session.

2.1 MUSIC Algorithm

MUSIC algorithm has the advantage over FFT as it overcomes the frequency resolution limitation in low signal to noise ratio. Let the data which is measured from the experimental setup is $x[t]$; this signal is assumed to be buried in a noise signal. Under no-load condition of the induction motor the healthy and the faulty stator currents are acquired for analyzing it. The autocorrelation matrix is calculated using the $N$ number of sampled data. The signal and noise subspace are separated using Eigen decomposition. Then the MUSIC algorithm is applied to obtain the pseudo spectrum.

$$x(t) = s(t) + e(t) \quad t=0,1,2,\ldots$$

$x(t)$ is the discrete time signals, $m$ complex sinusoids is $s(t)$ and a white noise $e(t)$, zero mean and a variance $\sigma^2$.

$$s(t) = \sum_{i=1}^{m} A_i e^{j2\pi f_i t}$$

$$A_i = |a_i| e^{j\theta_i} \quad (\text{4})$$

$A_i$ - ESDO, $f_i$ - The frequency, $|a_i|$ - The magnitude, $\theta_i$ - The phase of the $i$th complex sinusoid. The autocorrelation matrix $R_{xx}$

$$R_{xx} = \sum_{i=1}^{m} \sum_{j=1}^{m} \delta(i-j) \left|A_i\right|^2 F(f_i^*) F(f_i)= \left|F(f_i)\right|^2$$

$H$ - Hermitian transpose; $I$ - identity matrix.

$$F(f_i^*) = [1 e^{j0} e^{j(1)} e^{j(2)} e^{j(3)} \ldots e^{j(N-1)} e^{j(N-2)} e^{j(N-3)} \ldots e^{j(N-1)}]^{T}$$

MUSIC algorithm uses Eigen decomposition to separate signal and noise subspaces. According to Pisarenko harmonic Decomposition (PHD), the frequencies of sinusoids are estimated with the Eigen vectors corresponds to the smallest Eigen values of the auto correlation matrix.

Let the Eigen values and Eigen vectors of $R_{xx}$ are $\{\lambda_1, \lambda_2, \lambda_3, \ldots \lambda_L\}$ and $\{v_1, v_2, v_3, \ldots, v_L\}$ respectively. The Eigen vectors are classified into signal subspace vectors and noise subspace vectors. The signal subspace vectors are $\{v_1, v_2, v_3, \ldots, v_m\}$, associated with the largest eigen values. The noise subspace vectors are $v_{m+1}, v_{m+2}, \ldots, v_L$ that has the Eigen values as $\sigma^2$.

$$\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_m \geq \lambda_{m+1} = \ldots = \lambda_L = \sigma^2$$

In ideal case, it is assumed that the signal is buried in white noise. The signal related Eigen values are classified in decreasing order as follows: $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_m$, the noise related Eigen values are $\lambda_{m+1} = \lambda_{m+2} = \ldots = \lambda_L = \sigma^2$. But, in practical the noise is not completely white, and magnitudes of different components are different. Therefore

2.2 FSDO (m) Estimation

The MUSIC is a high-resolution frequency estimation method, whose performance is completely dependent on the Frequency Signal Dimension Order (FSDO) value ($m$). The FSDO ($m$) value depends on the number of sinusoidal components buried in the noise. Eigen values of auto correlation matrix help to estimate the FSDO value.

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it is difficult to classify the signal and noise values. The ordered model of Eigen values for a signal is shown in Figure 1. The signal contains different magnitudes of noise. Therefore, using criterion of minimum slope, the noise subspace is separated from the signals subspace. The relative slope variation between the two classes of noise subspace is very low.

![Figure 1. Ordered model of Eigen values for a sign.](image)

This is applied on discrete stator current samples of 1000 samples to examine 200 Eigen values (L=200). From Figure 1, it is known to us that for the Eigen values from k = 41 to 200, the slope variation is very low. Therefore, k=1 to 40 are associated with signal subspace and k=41 to 200 is associated with noise subspace. Therefore, the estimated value of FSDO is 40, as k=40 separate the signal and noise subspaces. The selection of m value is able to explore the information about the signal of interest. During analysis, taking lower or higher m value is able to neglect or include some interesting components.

3. Fault Detection with MUSIC Algorithm

In this session the expression for calculating the frequency components of the inter turn short circuit fault, experimental setup and experimental results are discussed.

3.1 Frequency Components Related to the Inter-Turn Short Circuit Fault

The current frequency \( f_{st} \) components related with the rotating fields for shorted turns are expressed as

\[
f_{st} = f_s \left( \frac{m}{p} (1 - s) \pm k \right)
\]

Where \( k = 0,1,3,5,\ldots \) \( m = 1,2,3,\ldots (2p-1) \)

\( p \) – Number of pole pairs, \( s \) – Per unit slip and \( f_s \) – Supply frequency. Since the number of pole pair is 2 \( m=1, 2\&3 \).

3.2 Workbench

The stator current data is acquired with a sampling frequency of 20000Hz, under healthy and faulty conditions from the 3 phase, 3 hp, 415V, 50Hz, 4pole squirrel cage induction motor. The faulty condition is artificially created with a very small modification in the connection of the motor winding.

The inter-turn incipient fault is created by connecting a resistance across the terminals which is to be shorted. This is equivalent to the partial insulation failure which is prior to the inter-turn short circuit fault. This indicates the inter-turn incipient short circuit fault which is shown in Figure 2. To prove the algorithm in estimating the severity of the fault, 3 different levels of faults are created. They are 3 turns short in R phase, 6 turns short in R phase and 3 turns short in R&Y phase.

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3.3 Result and Analysis

The frequencies of the stator current under healthy and faulty conditions are identified from the spectrum which in turn used in identifying the faults. Harmonics generated by these faults can have a wide frequency bandwidth. To observe the frequency components in the bandwidth [0Hz, 1kHz], MUSIC is used. In this section, the pseudo spectrum is presented to identify the inter-turn short circuit condition. After separating the signal and noise subspaces the pseudo spectrum is obtained using MUSIC algorithm. Figure 4 shows the pseudo spectrum of the healthy induction motor. Figure 5a, 5b & 5c show the pseudo spectrum of the induction motor under faulty conditions with 3 turns 6 turns shorted in R phase, 3 turns shorted in R&Y phase respectively.

In Table 1, the calculated and estimated frequency components of the induction motor under healthy and faulty induction motor are given. The frequency components associated with inter-turn short circuit faulty condition of the induction motor are calculated using equation (9). The frequencies associated with the faulty conditions are as follows: 25, 75, 125, 175 Hz with m=1; 100, 150, 200 Hz with m=2; 25, 75, 125, 225 Hz with m=3. The supply frequency is 50Hz.

The frequencies under healthy and faulty conditions are obtained with MUSIC algorithm. The fundamental frequency component is 50Hz. Additional harmonic components appearing in the pseudo spectrum are 10Hz, 20Hz, 30Hz, 60Hz, 100Hz, 225Hz, 625Hz and 925 Hz. These frequencies appear in the spectrum because of the rotor eccentricity faults, the standard misalignment, supply misalignment in phase and noise added with the signal. These are the standard frequencies which appear in the spectrum always.

The theoretical frequencies of faulty motor are estimated using equation (9) is verified with the pseudo spectrum estimation via MUSIC algorithm.

Figure 5a shows the harmonic components related to the 3 turns inter-turn short in R phase are, 25Hz, 75Hz, 100Hz, 125Hz, 650Hz, 750Hz, 775Hz, 925Hz (approximately). Along with these frequencies, some of the lower order frequencies which are less than 100 Hz also appear
in the spectrum as an indication of fault occurrence. It should be noted that the 50Hz supply frequency is also present but it is suppressed in the spectrum.

Figure 5b shows the harmonic components of the 6 turns inter-turn short in R phase are 25Hz, 75Hz, 175Hz, 200Hz, 400Hz, 750Hz, 875Hz, 925Hz and 950Hz (approximately). The lower order harmonics which is less than 100Hz appears in the spectrum. The supply frequency component is present and it is suppressed during fault occurrence suppressed in the spectrum.

The Figure 5c shows the harmonic components of the 3 turns inter-turn short in R&Y phase are 25Hz, 75Hz, 100Hz, 275Hz, 350Hz, 425Hz, 450Hz, 525Hz, 600Hz, 625Hz, 700Hz, 825Hz and 925Hz (approximately). The lower order harmonics which are less than 100Hz appear in the spectrum. The supply frequency is present in the spectrum but it is suppressed.

The frequencies obtained from the pseudo spectrum of the MUSIC algorithm approximately match the frequency values calculated using equation (9). As the severity of the fault increases, the harmonic frequencies included in the signal also increases.

Table 1. Frequencies calculated and estimated for the healthy and faulty conditions

| Calculated Frequencies (Hz) | Estimated frequencies from the pseudo spectrum (Hz) |
|-----------------------------|--------------------------------------------------|
| 25, 50, 75, 100, 125, 150, 175, 200, 225…... | Healthy 10, 20, 30, 50, 60, 100, 225, 625 and 925 |
| 3 turns short in R phase     | 25, 50, 75, 100, 125, 650, 750, 775, 925         |
| 6 turns short in R phase     | 25, 50, 75, 175, 200, 400, 750, 875, 925 and 950 |
| 3 turns short in R&Y phase   | 25, 50, 75, 100, 275, 350, 425, 450, 525, 600, 625, 700, 825 and 925Hz |

Note: 50Hz is the supply frequency; Along with the frequencies specified in the faulty conditions, some of the lower frequencies (less than 100Hz) also appears in the spectrum.

4. Conclusion

From the stator current signal which is buried in the noise, MUSIC algorithm is used to identify the inter-turn incipient short circuit fault. The frequencies of the stator current signal under healthy and faulty conditions are estimated with the pseudo spectrum of the MUSIC algorithm. These frequencies are compared with the calculated frequencies to prove the results. The comparison between the calculated frequencies and the frequency estimated from the pseudo spectrum is able to prove the accuracy of the proposed algorithm compared with traditional FFT algorithm.

As the size of auto correlation matrix increases the computational complexity of high resolution technique increases.

5. References

1. Nandi HA, Xiaodong TL. Condition monitoring and fault diagnosis of electrical motors - A review. IEEE Transaction on Energy conversion. 2005 Dec; 20(4):719-29.
2. Memala WA, Rajini V. Park's vector approach for online fault diagnosis of induction motor. International Conference on Information Communication and Embedded Systems (ICICES). 2013 Feb; p. 1123-29.
3. Memala WA, Rajini V. Induction Motor Fault Diagnosis using Lab VIEW. International Conference on Circuits, Power & Computing Technologies, ICCPCT 2013. 2013 Mar; p. 176-79.
4. Bonnett A, Yung C. Increase efficiecy versus increase reliability. IEEE Industry Application Management. 2008 Feb; 14(1):29-36.
5. Cusido J, Romeral L, Ortega JA, Rosero JA. Increase efficiency versus increase reliability Increase efficiency versus increase reliability. Montreal, Quebec, Canada: IEEE Imperial Society of Innovative Engineers. 2006; 3:2406–11.
6. Daviu JAA, Guasp MR, Folch JR, Palomares MPM. Validation of a new method for the diagnosis of rotor bar failures via wavelet transform in industrial induction machines, IEEE Transaction on Industry application. 2006 July/Aug; 42(4):990-96.
7. Kia SH, Henao H, Capolino GA. A high-resolution frequency estimation method for three-phase Induction machine fault detection. IEEE Transaction on Industry Electronics. 2007 Aug; 54(4):2305-14.
8. Bouzida A, Touhami O, Ibtouen R, Belouchrani A, Fadel M, Rezzoug A. Fault diagnosis in industrial induction machines through discrete wavelet transform. IEEE Transaction on Industry Electronics. 2011 Sept; 58(9):4385-95.
9. Hwang DH, Yoon YW, Sun JH, Kim YH. Robust diagnosis algorithm for identifying broken rotor bar faults in induction motors. Journal of Electrical and Engineering Technology. 2014; 9(1):37-44.
10. Memala WA, Rajini V. Information Theoretic Criteria for Induction motor fault identification. Indian Journal of Science and Technology. 2015 Nov; 8(30):1-6.
11. Young YW, Yi SH, Hwang DH, Sun JH, Kang DS, Kim YH. MUSIC based diagnosis algorithm for identifying bro-
ken rotor bar faults in induction motors using flux signal.
Journal of Electrical and Engineering Technology. 2013;
8(2):288-94