Induction Machine Stator winding Failure
Detection Using Motor Current Signature Analysis

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Abstract: In addition to the domestic applications, developments in power converter topologies and governments focus on developing renewable energy sources, Induction machines use increases gradually. Earlier wind farms used Squirrel cage induction generators and now the doubly fed Induction generators replaced the SQIMs because of the flexibilities and controllable opportunities they have. But due to rapid fluctuations in speed and power flows stator windings prone to high electrical stresses and leads to outages. In this article wavelet based current signature analysis method adopted to investigate the induction machines fault frequencies. Discrete wavelet transform, stationary wavelet transforms and wavelet packet decompositions are used for the said purpose. The wavelet decomposition is used to pull out the information on a signal over a ample range of frequencies. Analysis is carried out in both time and s domains. The stator current analysis is done using the daubechies wavelets. Stator windings inter turn faults considered and simulated in simulink.

1. INTRODUCTION
The motors used in the industrial applications should have the following properties like low cost, low maintenance, variable speed control, compact in size, ruggedness and to be able to work under any operational circumstances. Induction motor is one of the motor which can full fill the above properties. Despite of its merits like rugged construction and high precision, electrical stresses in stator and rotor windings causes internal faults due exceeding thermal limits[1]. Of these stator faults are more ubiquitous and potentially vicious leading to the motor failures thus insulation break down can be as high as 30%-40% [1]-[2] is shown in figure 1. In most of the situations these stator inter-turn insulation fault begins as a minor and often go hidden, which may ultimately grow and lead to major once[3]. Majorly this insulation degradation occurs under abnormal electrical, thermal, mechanical under different environmental stress [4][26].

Figure 1. Distribution of faults in induction motor
The foremost intention is to extend schemes for reliable detection of faults at primary stage itself, which will allow a systematic and controlled maintains instead of rapid failure, thus dipping production losses outage time and injury to the instrumentation as per industrial surveys and supported alternative eventualities. Large percentages of failure in induction motors results from the stator failures which is ranking second after the baring failure [5]. In the time of yore whenever a machine experience some fault it can be detected by some simple techniques such as over current or over voltage detection [28] of which these techniques required the machine to be in off line in order to clear the fault[6], but as of in the safety-critical applications, the shutdown of running motor is not an acceptable thing. This demands a better fault detection and remediation strategies [7].

2. MOTOR CURRENT SIGNATURE ANALYSIS (MCSA)

MCSA measures the most popular fault detection method [8]. MCSA is well popularized as it gives the machine condition without affecting or interrupting its process usage. Giving status of rotating induction machine based on stator current, which can be obtained easily is another value added advantage. Digital technologies made easy sampling required Current measurements at required intervals[9]. Now a day’s simple detect the normal faults in stator[10]. The example established in this paper includes many at the potential applications offered through execution of the motor diagnostic technologies. The basic principle behind unique expansion of MCSA technologies of the detection of stator faults[11].

In the stator fault current is shown in figure 2 in the region of the base frequencies, the inter turn short produces same frequencies in an induction motor are given by

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

(1)

Where \( f_s \) is that the base frequencies \( m=0,1,2,3 \) and \( k=0,1,3,5 \), \( p \) is that the range of pole pairs and \( s \) is that the percentage unit slip the frequencies may be analyzed exploitation any frequencies domain signal process technique[12]. In order to remove the inter turn faults, this method employs frequencies analysis using different types of wavelet transforms for fault diagnosis in an induction motors [23] frequencies corresponding related to definite combinations of \( k \& m \) in eqn (1) is used for brief circuit fault analysis as a result of the prevalence of voltage disturbs and different asymmetries

| K=0 | K=1 | K=3 | K=5 |
|-----|-----|-----|-----|
| M=0 | 0+50,-50 | +150,-150 | +250,-250 |
| M=1 | 24.6 | 74.6,-25.4 | 174.6,-125.4 | 274.6,-225.4 |

Table 1. fault frequencies

![Figure 2. Faulted frequency current wave form](image)

Figure 2. Faulted frequency current wave form
3. PROPOSED METHOD

![Diagram 3. A Notch filter based wavelet analysis for a three phase induction motor](image)

3.1 System Description

The configuration of notch filter-based wavelet analysis for a three-phase induction motor shown in Figure 3. The stator current from the three-phase induction motor is fed to the notch filter. And the wavelet analysis is performed with and without notch filter in order to diagnose the faults and both of them are compared in the comparison block. This data is used for making the decision algorithm.

3.2 IIR Notch Filter

IIR filter states to Infinite Impulsive Response. A notch filter may be a band-stop filter with a slim stop band (high alphabetic character factor). Because of external disturbances in setting, system creates unwanted frequencies referred to as noise. Factors poignant Annoyance area unit as follows Primary Acoustic: Sound level, frequency and period; Secondary Acoustic: Spectral complexity, fluctuations in frequency level, localization of noise supply. Non-acoustic: Adaptation and past expertise, listener’s activity interference, certainty of noise, individual temperament [13]. Louder is that the noise the larger is that the annoyance. Detection of clanging curving signals and its adaptive frequency estimation area unit essential in communications, radar, sonar, controls, and medicine signal process systems. Adaptive IIR notch filters are with success used for detection curving signals in wide-band noise. Generally, Associate in Nursing adaptive IIR notch filter is most popular because of its less range of filter coefficients and therefore less procedure complexity [14]. The output of the fault signal by mistreatment the IIR notch filter is shown in figures 7, 8 & 9. Notch filter take approach the interference at 50Hz and its harmonics alone. IIR notching filter eliminated \( F_0 = \) fifty cycle per second frequency center frequency with quality issue \( Q=5 \). BW = \( F_0/Q \). [15].

3.3 Different types of wavelet methods.

3.3.1. Discrete wavelet transforms (DWT)

It is a tool that varieties data into different frequency components, and then studies each component with resolution corresponding to its scale. DWT computes with a cascaded filtering followed by a factor two sub sampling[16]. In this paper, daubechies is a mother wavelet. This wavelet is compared with the fault signal in order to identify the fault location of the signal. To evaluate the frequency components of the signal, the Fourier transform is one of the useful tool. But the main drawback is over the whole time axis we cannot notify at what instant an exact frequency rises[17]. Wavelet transform is based on varying frequency of the small wavelets in a limited duration. In this paper, scaled version wavelet transform has been investigated. In this DWT method we have two types of coefficients is shown in figure 4. One is approximation coefficient and the other is detailed coefficient. Of this detailed coefficient is considered in this paper, where it can decompose 8 levels of the fault signal.
Among these 8 levels the two levels 5&7 indicates exact fault location of the faults in with and without notch filter results is shown in figure 7.

![Figure 4. Decomposing levels of DWT](image)

Signal and other levels 4,6&8 indicates the average location of the fault signal, whereas the levels 1,2&3 fails to indicate the fault location of the fault signal.

### 3.3.2. Stationary wavelet transform (SWT)

In this part, how the basic DWT algorithm can be adapted to give a stationary wavelet transform explained. The SWT is a time invariant transform, is analogous to DWT however the sole process of down-sampling is suppressed, instead up-sampling the filters by inserting zeros between the filter coefficients[18]. SWT provides redundant, linear and shift invariant transformation in this SWT method we have two types of coefficients is shown in figure 5 one is approximation coefficient and the other is detailed coefficient [19]. Of these detailed coefficient is measured in this paper, where it can decompose 8 levels of the fault signal. Using SWT we can identify the fault coefficients. The eight levels of decompose the signal the levels 3,6,7 and 8 having good indication for without and with notch filer results is shown in figure 8 respectively by decomposing the eight levels, the four signal levels shows good indication i,e 3,6,7 and 8. Compare to DWT, the SWT has good indication for the fault.

![Figure 5: Decomposing levels of SWT](image)

![Figure 6: Decomposing levels of WPD](image)

\[ G^l = \text{high pass filter at level}; \quad H^l = \text{low pass filter at level}; \quad l = \text{sample number} \]

The figure 5 shown above will decompose up to n levels. This decomposition has no down samplings.
3.3.3. Wavelet Packet Decomposition (WPD)

Wavelet packet decomposition is a method in wavelet transform where the signal is sent through multiple filters[20]. The algorithm of discrete wavelet packet transform is executed by two-channel filter banks having a half-band low pass filter and high pass filter pair. The study of a signal is processed out by first decomposing the signal in to a low pass and then high pass filtering repeatedly as shown in figure 6. In the DWT, each level is estimated by sending the previous approximation coefficients through a high and low pass filters[21]. Based on ranking, the signal to be programmed is successively split into high and low frequency modules. The number of progressions is usually limited by the desired level of frequency resolution and available computational power.

The frequency ordering of the wavelet packet coefficients are quite in binary gray code sequence. The output of any two channels analysis is the result of low and high pass filtering followed by down sampling which in turn reduced by an order of two[22]. In this paper, the fault frequencies of the signal nodes is 8th level 1st node and 8th level 6th node of the without and with notch filer decomposition is shown in figure 9. Exact fault location is deducted by using this method.

| Without Notch Filter | With Notch Filter |
|----------------------|-------------------|
| **level** | Healthy | Faulty1 | Faulty2 | Faulty3 | Healthy | Faulty1 | Faulty2 | Faulty3 |
| Level-1 | 0.1797 | 0.183 | 0.184 | 0.1824 | 0.1854 | 0.1826 | 0.1816 | 0.1798 |
| Level-2 | 0.1821 | 0.1805 | 0.1818 | 0.1854 | 0.1828 | 0.1812 | 0.1875 | 0.1812 |
| Level-3 | 0.1041 | 0.2036 | 0.2059 | 0.2057 | 0.1726 | 0.1778 | 0.1757 | 0.1677 |
| Level-4 | 0.4862 | 0.4761 | 0.4844 | 0.5286 | 0.1258 | 0.1296 | 0.1305 | 0.1304 |
| Level-5 | 0.789 | 0.8018 | 0.8021 | 0.8088 | 0.1398 | 0.1411 | 0.1496 | 0.1692 |
| Level-6 | 0.6305 | 0.606 | 0.6108 | 0.6062 | 0.2585 | 0.2256 | 0.2253 | 0.2976 |
| Level-7 | 7.139 | 7.167 | 7.174 | 7.1477 | 0.6881 | 0.7617 | 0.7914 | 0.8363 |
| Level-8 | 2.4082 | 2.3769 | 2.3363 | 2.366 | 0.6388 | 0.64 | 0.6034 | 0.6933 |

**Table 2.** Standard deviation values of DWT

| Without Notch Filter | With Notch Filter |
|----------------------|-------------------|
| **level** | Healthy | Faulty1 | Faulty2 | Faulty3 | Healthy | Faulty1 | Faulty2 | Faulty3 |
| Level-1 | 3.7401 | 3.4586 | 3.6499 | 4.2482 | 1.9248 | 1.1931 | 1.9432 | 2.193 |
| Level-2 | 2.3773 | 2.3802 | 2.4214 | 2.3742 | 0.6053 | 0.6004 | 0.6192 | 0.5992 |
| Level-3 | 2.1366 | 2.0792 | 2.0801 | 2.1556 | 0.4905 | 0.5037 | 0.4575 | 0.6253 |
| Level-4 | 9.5958 | 9.6465 | 9.6395 | 9.5637 | 0.8394 | 0.8322 | 0.8244 | 0.8091 |

**Table 3.** Standard deviation values of SWT
Fault current = \frac{\text{Fault Standard deviation}}{\text{Healthy Standard Deviation}} \tag{2}

By using equation (2), the wavelet analysis is performed to the stator current based on the faulty and healthy standard deviation values in order to find out the fault current.

### Table 4. Standard deviation values of WPD

| Level   | 0.1973  | 0.2065  | 0.2089  | 0.2478  | 0.2143  | 0.1525  | 0.2062  | 0.1427  |
|---------|---------|---------|---------|---------|---------|---------|---------|---------|
| Level-5 | 0.3043  | 0.2961  | 0.2522  | 0.2947  | 0.1864  | 0.1922  | 0.1956  | 0.199   |
| Level-6 | 0.5337  | 0.4795  | 0.524   | 0.525   | 0.3495  | 0.3758  | 0.3557  | 0.5     |
| Level-7 | 0.9981  | 1.0307  | 1.0341  | 1.775   | 0.2034  | 0.1981  | 0.1849  | 0.2096  |
| Level-8 |         |         |         |         |         |         |         |         |
Figure 9. Standard deviation ratio of faulty stator currents from WPD analysis (a) without notch filter (b) with notch filter

4. CONCLUSION
This paper described about the MCSA method in induction motor. This method is highly adaptable, reliable and more flexible for condition monitoring and fault frequencies levels. In order to find the magnitudes of fault levels different wavelets were implemented and for reducing the noise in the fault signal IIR notch filter used. One of the main advantage of this MCSA is it can detect the faults at an early stage and these helps in avoiding the inferior damage and complete failure of the motor.

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