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Impact of Sampling Rate Variations on Signal Spectrum Based Fault Diagnosis of Induction Motor

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Abstract

The investigation looks into how sampling rate variations affect induction motors fault diagnosis based on signal spectrum analysis. Modern companies depend heavily on induction motors, but they can develop mechanical and electrical problems that, if not found quickly, can result in significant financial loss and downtime. Fault identification relies heavily on signal processing techniques, particularly Motor Current Signature Analysis (MCSA). The Fast Fourier Transform (FFT) technique for frequency spectrum analysis is the main topic of this work. This study investigates how the FFT spectrum is affected when sample rates are changed using decimation and interpolation techniques, with a focus on the diagnosis of broken rotor bar (BRB) problems in induction machines. The methodology involves determining acquisition parameters, calculating the required sampling rate, performing interpolation and decimation, and applying FFT with proper window functions. Spectral leakage, a common issue in FFT-based techniques, is addressed using Hann window function. Experimental results are presented for a healthy motor, a motor with one BRB at different loading conditions, and a motor with BRB at no load. The study compares original sampling rates of 20 KHz obtained from experimental setup in laboratory and with resampled sampling rates using purposed methodology. The findings emphasize the importance of choosing an appropriate sampling rate based on fault visibility and computational efficiency.

Keywords

Induction Motor, Fault Diagnosis, Broken Rotor Bar, Fourier Transform

1. Introduction

Since the second industrial revolution started, induction motors have become really important in modern industries. They are used in various ways, like generating power and in things we use every day. For example, they play a crucial role in renewable energy sources like wind power plants. Induction motors also help convert electrical energy into mechanical energy, driving many industries and impacting a country's economy. They're widely used in everyday things like electric vehicles, fans, water pumps, and more. While there are other machines that can do the same job, induction motors are popular because they are simple, efficient, and easy to fix. They use a lot of electricity, about half of the total generated worldwide [1]. These equipment feature moving parts, which makes them prone to malfunctions. There are two primary categories of these issues: mechanical and electrical. Electrical faults, which include inconsistent voltage, phase drop, short circuits between turns, and grounding issues, are mostly associated with the stator. Most faults are mechanical in nature, and include things like broken end rings, rotor bars, and damaged bearings, as well as faulty part positioning. These faults are directly or indirectly related with each other and are degenerative in nature. Hence, it is very important to detect them at an incipient stage in order to avoid extensive economic loss and time-consuming repair processes.

Electrical machine diagnostics today employ a variety of faults detection techniques. Advanced signal processing methods are essential for predicting engine maintenance requirements. There has been a discernible shift in the development of digital technology during the last few years. This change makes it possible to use reasonably priced hardware platforms that have efficient data processing capabilities. These hardware platforms can be used to enhance the performance of real-time diagnostic systems in addition to identifying instant messaging malfunctions [2]. Determining the best methods for signal processing is crucial to determining whether induction motor (IM) maintenance is required. Predicting maintenance can cut down on expenses and repair time for instant messaging. Scholars across the globe are investigating several approaches to accomplish this. Spectral Kurtosis (SK), Park's Vector Approach (PVA), Wavelet Transform (WT), Empirical Mode Decomposition (EMD), Singular Value Decomposition (SVD), Hilbert Transform (HT), Wigner-Ville Distribution (WVD), Principal Component Analysis (PCA), Independent Component Analysis (ICA), and Kalman Filter (KF)are just a few of the widely used techniques.

The major goal of any signal processing techniques was to identify any new frequencies in the overall signal of the system that would point to a fault. In order to locate and save the tiny, delicate, and crucial information linked to faults, researchers spent a great deal of time developing signal processing systems. They concentrated on improving the spectrum resolution under both steady state and dynamic conditions. This was a shared objective to enhance our ability to recognize and address machine problems. A significant number of AI-based research are also being done and number is increasing. The accuracy and maturity of AI- algorithm depends on the data size [3]. Thanks to different mathematical modeling like Finite Element Method (FEM) [4], data collection is possible using simulation. But the collection of large set of data at higher sampling rate for better spectral resolution and accuracy is issue for both simulation and experimental set up. It comes with calculation complexity and memory storage requirement. The data acquisition at higher sampling rate in real time diagnosis of fault in industrial machine is also not economical [3]. This is not a parameter that can be easily adjusted [5].

This paper describes how to change the initial sample frequency by decimation and resampling, and it shows how change in sampling rates affect the signal's frequency spectrum for diagnosing broken rotor bar (BRB) faults in induction motor in various scenarios.

2. Background

Motor current signature analysis (MCSA) based fault diagnostic techniques are being extensively used in research, because these techniques are mostly noninvasive in nature and require simple measurements [6]. After the current measurement, there comes an entire domain of signal processing techniques to estimate the nature and the severity of the fault. The fast Fourier transform (FFT) one of the most utilized signal processing methods for these purposes [7]. In this paper FFT is used to study the frequency spectrum of current signal obtained from the experimental set up of healthy motor and induction motor with broken rotor bars.

Depending on the defect's severity, each failure causes a different frequency and modulation index in the stator current. The geometric and electrical parameters of the rotor and stator determine the mathematical representation of these fault frequencies. Early detection of a broken bar is crucial because when one breaks, the subsequent bars are subjected to increased thermal stress, which may lead to their failure. Certain harmonics in the frequency spectrum are produced by these faults [8].

$$f_{br} = f_s \pm 2ksf_s \tag{1}$$

$$f_{br} = [(k/p)(1-s) \pm s] f_s \tag{2}$$

where k = 1,2,3........., f_s is supply frequency, s is the slip and p is the no of poles pairs of the machine. The fault-related harmonics are denoted as the left side band (LSB) and right side band (RSB). These fault harmonics can be buried under fundamental frequency spectrum because of their dependency on slip. These problem is more severe for the motor running under the low load condition.

2.1 Fast Fourier Transform

In numerous scientific fields, the Fast Fourier Transform (FFT), is a useful tool. It assists in splitting an erratic signal into distinct components known as sinusoids. Amplitude is the term used to describe the frequency and size of these sinusoids. These sinusoids typically get smaller in size as we examine across a range of frequencies. The foundational component is the most significant. This process is represented mathematically by formulas known as the discrete Fourier transform (DFT) and its inverse.

$$X_k = \sum_{n=0}^{N-1} x_n \, e^{-\frac{j2\pi kn}{N}}, \; k = 0,1,2,...(N-1) \tag{3}$$

$$x_n = \frac{1}{N} \sum_{n=0}^{N-1} X_n \, e^{-\frac{j2\pi kn}{N}}, \; k = 0,1,2,...(N-1) \tag{4}$$

where k is the current frequency, N is the number of samples, n is the current sample, x_n is the signal value at time n, and X_k is the DFT resulting bin.

2.2 Interpolation

The technique of guessing or projecting values between current data points in a signal is known as interpolation. Put otherwise, it's a technique for adding to or filling in the blanks within a range where the initial signal values are known. There are various interpolation methods, and the method of choice is determined by the particular needs and signal characteristics. Spline interpolation, cubic interpolation, and linear interpolation are a few popular interpolation techniques.

If the interpolation is done by n times, the new frequency of sampling is increased by f_r=nf_s along with the bandwidth (BW). Where, f_r is new resampled frequency and f_s is original sampling frequency.

2.3 Decimation

The process of decimation involves lowering the amount of samples in a signal, usually by deleting some of the samples on purpose. It is the interpolation process done in reverse. Decimation is the process of lowering the number of samples to get a lower sampling rate, whereas interpolation entails predicting values between current samples to increase the number of data points.

Mathematically, The relationship between the initial sampling rate (f_s) and the new sampling rate (f_d) following decimation can be expressed as f_d=$\frac{f_s}{m}$ along with the bandwidth (BW). where m is the decimation factor which can be chosen according to the requirement.

Hence, using interpolation and decimation we can perform fractional resampling as:

$$f_r = \frac{n}{m} f_s \tag{5}$$

And the frequency resolution $\nabla f = \frac{f_s}{N}$, where f_s is sampling frequency and N is the no of input data samples. From equation (5) the value of n and m or N can also be choose in such a way that the fundamental frequency will be equal to the exact integer multiple frequency resolution which also helps in reducing the effect of spectral leakages for FFT based techniques [5].

2.4 Methodology

The following is the intended methodology for altering the signal's sample rate through the use of intended techniques:

1. Find the acquisitions parameters like sampling frequency f_s, fundamental frequency of the signal and sampling length N.
2. Determine the required sampling rate f_r.
3. Using Eqn.5, determine the integer value of n and m and proceed to interpolate n times.
4. Decimate the interpolated signal m times to get the required sampling rate.
5. Find the FFT of the resampled signals using proper window functions (Hann Window).

When spectral energy from a signal spills into nearby frequency bins, it's called leakage. Because window functions taper the signal towards the endpoints, they assist reduce leakage. For this, functions like Hann and Hamming are frequently employed. For this research Hann window function is used to perform the signal analysis. Spectral leakage is one of the major problem of FFT techniques which has not been sufficiently studied [9]. When two characteristic frequencies are positioned closely together, spectral leakage becomes more noticeable because the spurious components of both frequencies interfere with each other. This condition frequently occurs when broken rotor bar detection occurs in induction motors, especially when the motor is operating with a low mechanical load, changing loads, or low-frequency load oscillations. In these cases, the fault's characteristic frequency nearly matches with the main frequency. The spectral leakage caused by the main frequency interferes with spectral components that are close together, like those linked to broken rotor bars, if the main frequency does not match specific requirements, as stated by equation (5). While total reduction of leakage is not possible, it can be reduced by employing a Hann window [5].

3. Experimental Results and Discussion

The motor input current of healthy motor and motor with one and two broken rotor bars(BRB) at different loading conditions were obtained from experimental setup. The motor bars were drilled to simulate the BRB. Initially the current data is obtained at sampling rate of 20kHz initially. Following cases are studied at different sampling rates.

3.1 Case A: Healthy motor at 100% of the rated load.

The first case of the study is done for healthy motor at 100% of the rated load. The motor is fed from the grid supply of frequency 50Hz. The original sampling frequency is 20 KHz and study is done at 2 kHz and 32 kHz using purposed method. The original data length is 4×10^6. The nearest power of two to the data length is N= 2^{18} = 262144. Figure 1 gives the FFT of the healthy motor using Hann window and without using Hann window at sampling rates of 2 KHz (m=10, n=1), 20 KHz (original) and 32 KHz (m=5, n=8). The spectrum is zoomed at near the fundamental region. The resampled sampling frequencies are calculated using purposed method. The window length for 2 KHz and 32 KHz is 16384 and 524288. It shows that the spectrum of the signal using Hann window is sharper than without using. It also shows that the more the sampling rate sharper the spectrum of the signal.

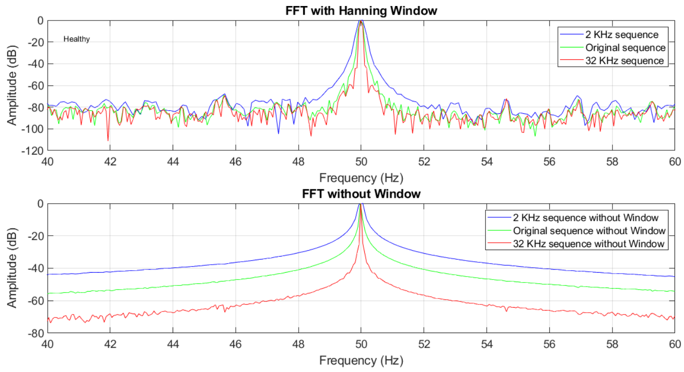
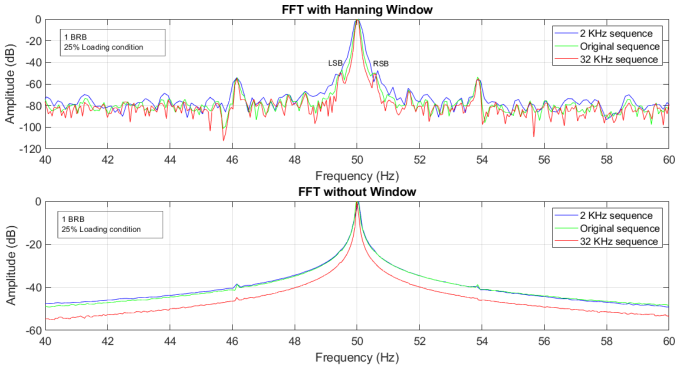


Figure 1: FFT spectrum of original and resampled data signal for healthy motor at 100% of rated load with and without Hann window

3.2 Case B: Motor with 1 BRB at 25%, 50% and 100% of the rated load.

The second case study is done for Induction motor with one broken bars for three loading condition: 25%, 50% and 100% of the rated load. The study is done for original sampling rate (20KHz), 2 KHz and 32 KHz. The window lengths are same as previous case. Figure 2 shows the FFT spectrum for different sampling rate at different loading condition. The spectrums are zoomed in region of interest which is near fundamental frequency as the fault bands due to broken bar can be seen near fundamental frequency. In Figure 2a for 25% loading condition, without window we cannot see any LSB or RSB. With Hann window the LSB and RSB for the sampling rate of 20 KHz and 32 KHz are clearly shown but these components are shown in a sharper way can be easily distinguish but we cannot see LSB of 2 KHz sequence clearly. Similarly Figure 2b shows the spectrogram of the signal for 50% loading condition and Figure 2c shows the spectrogram of the signal for 100% loading condition. Figure 3 shows comparing spectra obtained at 32 KHz and 50 KHz sampling rates reveals minimal enhancements in spectrum sharpness despite increased computational time and memory usage. Utilizing MATLAB 2023b with an Intel Core i5 processor, simulation times for 25% loading condition with 1 BRB were 0.54181 seconds and 0.7213 seconds, with memory usage at 117.8948 MB and 186.0962 MB, respectively. While higher sampling rates may marginally improve spectral resolution, the associated computational burden may not always justify the benefits, particularly when spectral differences are negligible.Recognizing that the presented simulations represent single-case scenarios, future research should encompass diverse cases and multiple iterations to comprehensively understand the sampling rate's impact on fault diagnosis accuracy and efficiency.



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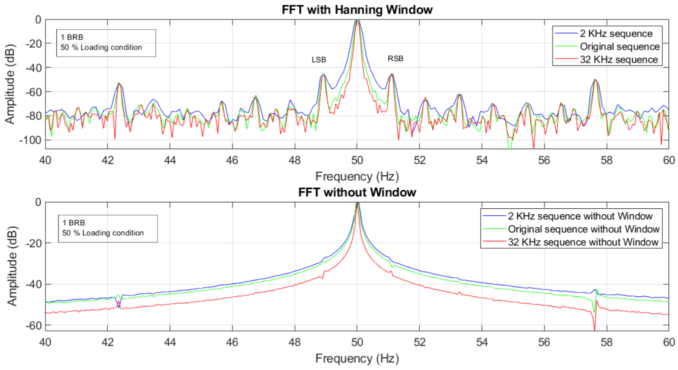

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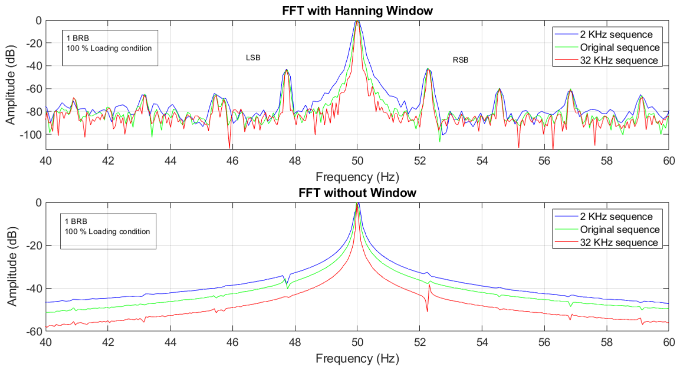


(c)

Figure 2: FFT spectrum of original and resampled data signal for motor with 1 BRB with and without Hann window. a) at 25% loading, b) at 50% loading, c) at 100% loading

3.3 Case C: Motor with broken rotor bar at no load

In this study the data obtained from the motor with broken rotor bar at no load condition is studied. As slip at low load condition is very low which means the LSB and RSB are very near to fundamental frequency and their amplitude is very weak compare to the amplitude of fundamental component which decreases the visibility of fault based harmonics. Figure 4 shows the spectrum of the data at no load condition for different sampling frequency. From the plot we can see that at no load it is very difficult predict which spectrum is faulty and which one is healthy as the spectrum of healthy and faulty condition are almost identical. Even if we resampled the original sampling rate the fault harmonics cannot be seen.

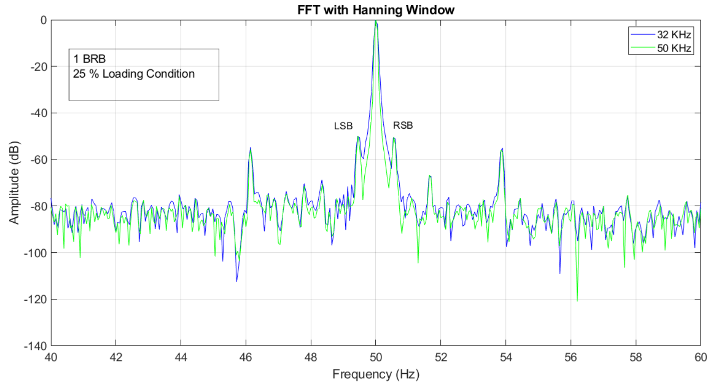
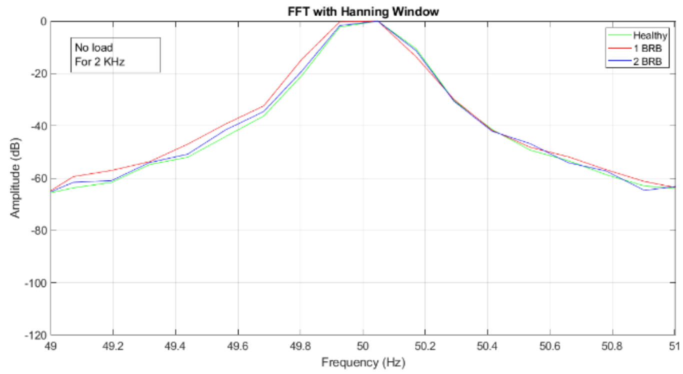


Figure 3: Comparison of FFT spectrum of 32 KHz and 50 KHz data signal for motor with BRB1 at 25% loading condition.



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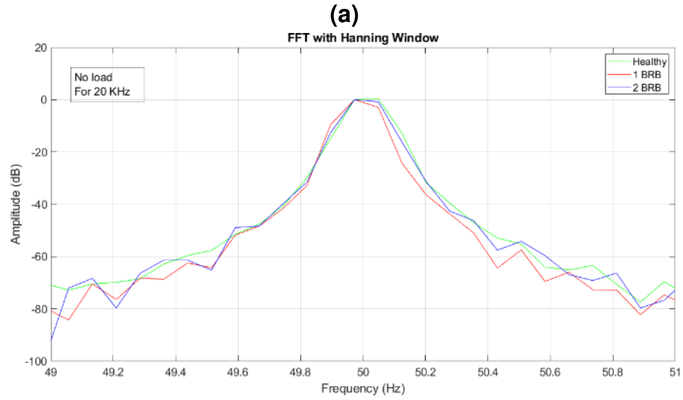

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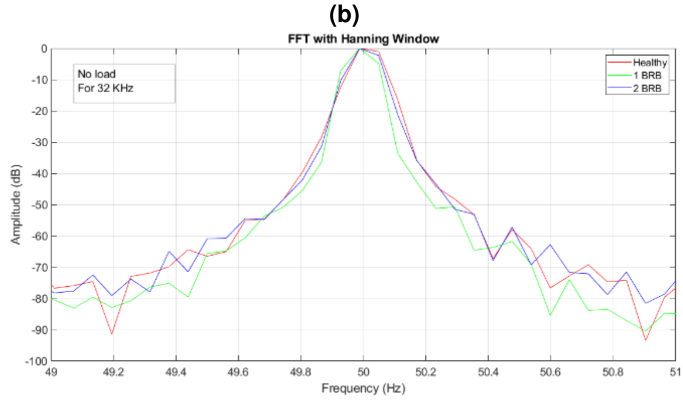

(c)

Figure 4: FFT spectrum of the healthy and motor with broken rotor bars at no load for different sampling rates of input signal, a)for 2 KHz, b) for 20 KHz, c) for 32 KHz

4. Conclusion

The analysis highlights the significance of sampling rates in signal spectrum-based fault diagnosis of induction machines. The study demonstrates that changing sampling rates can affect the visibility and sharpness of fault-related harmonics in the FFT spectrum. The use of Hann window functions proves effective in mitigating spectral leakage issues. The results emphasize the need for a careful selection of sampling rates based on fault characteristics and computational considerations. Higher sampling rates may not necessarily improve fault detection and can lead to increased computational complexity without significant benefits. In conclusion, the research provides valuable insights into optimizing sampling rates for fault diagnosis in induction machines, contributing to the development of efficient and reliable diagnostic systems for industrial applications.

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