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Utilizing Short-Time Fourier Transform for the Diagnosis of Rotor Bar Faults in Induction Motors Under Direct Torque Control

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ABSTRACT

Industrial applications rely heavily on induction motors (IMs). Even though any IM problem can seriously impair operation, rotor bar failures (RBFs) are among the toughest to identify because of their detection challenges. RBFs in IMs can significantly impact performance, leading to reduced efficiency, increased vibrations, and potential IM failure. This research provides a thorough analysis of diagnosing these issues by detecting RBFs and evaluating their severity using three sophisticated signal processing techniques (Fast Fourier Transform (FFT), Short-Time Fourier Transform (STFT), and Discrete Wavelet Transform (DWT)). The three techniques (FFT, DWT, and STFT) are used in this work to assess the stator currents. An accurate mathematical model of the IM under RBFs serves as the basis for the simulation. The robustness of Direct Torque Control (DTC) is assessed by examining the IM's behavior in both normal and malfunctioning situations. Although the results show that DTC successfully preserves motor stability even when there are flaws, the current analysis offers some significant variation. The findings show that when it comes to identifying RBFs in IMs and determining their severity, the STFT performs better than FFT and DWT. The suggested method maintains low estimation errors and strong performance under various operating situations while providing high failure detection accuracy and the ability to discriminate between RBFs.

1. Introduction

Due to their high reliability, cost-effectiveness, and robustness, induction motors (INMs) are widely used in industrial environments [1]-[6]. However, like any other electromechanical system, they are susceptible to faults that can lead to unexpected failures and reduced performance. Among these, rotor bar faults are particularly critical, as they cause torque oscillations, increased losses, unbalanced magnetic fields, and INMs overheating [7]-[11]. Because of their effectiveness, longevity, affordability, and minimal maintenance needs, INMs are regarded as the most significant and extensively utilized INMs in practically all industries. They are essential to modern industry since they are involved in many different areas, such as production, transportation, and home appliances. INMs' position as the foundation of industrial applications is further cemented by the fact that they frequently come with power electronic converters to handle speed control concerns. INMs are crucial, as evidenced by the fact that they are used in about 70% of industrial applications [12]-[17].

Notwithstanding their resilience, INMs are susceptible to a range of physical issues brought on by warm air, motorized, and electric stressors. These issues can interfere with regular operations, resulting in large financial losses, decreased production, and expensive emergency repairs [18]-[23]. Fault data show that about 10% of the inside electric failures in INMs are rotor problems, while about 37% are stator defects. Over 36% of INM stator failures are caused by stator turn-to-turn, or inter-turn faults (ITFs), which make up a sizable fraction of the various fault categories [24]-[26]. ITFs are especially important since they can cause serious harm very quickly, making early detection essential to avert unplanned malfunctions and guarantee system dependability. Because they assist in preventing possible damages, saving downtime, and increasing the working lifetimes of these INMs, effective methods for identifying internal problems in INMs are therefore crucial for modern industry. Model-based techniques (MBTs), signal analysis-based techniques (SABTs), and artificial intelligence-based techniques (AIBTs) are the three main strategies for identifying ITFs in INMs [27]-[30]. To find differences suggestive of problems, model-based approaches entail building a mathematical model of the INM and contrasting it with its real behavior [31]-[36]. These techniques demonstrate important developments in MBT fault identification. High accuracy, flexibility in response to changing circumstances, and efficient fault separation are the main benefits. These methods do, however, have drawbacks, including the requirement for exact parameter adjustment, computational complexity, implementation difficulty, and dependence on intricate INM settings.

Early detection of RBFs is essential for preventing system breakdowns and enhancing maintenance planning. Traditional fault detection techniques mainly rely on mechanical and thermal monitoring; however, these methods can be costly and inefficient for early-stage detection. Stator current analysis has emerged as a powerful, non-invasive diagnostic technique capable of identifying faults by examining variations in current signals [37]. The difficulties with MBTs' diagnosis have led to the development of several SABTs. These methods examine particular electrical signal properties to find anomalies that point to the existence of problems. The usefulness of SABTs is demonstrated in [31], who emphasize the significance of INM current signature analysis (INMCSA) and DWT for detecting frequency shifts in the INMC under fault situations. Similar to this, [38] extracted pertinent features from INMC and voltage signals and used INMCSA in combination with harmonic analysis to diagnose stator winding defects, including inter-turn short circuits (ITSC). By employing AIBTs and studying current waveforms, [39], [40] highlighted the possibility of MCSA for ITF detection. A technique for identifying ITSC failures using zero crossing instant (ZCI) analysis was presented in [41], albeit its efficacy might be reduced in noisy environments or with different load profiles. For defect detection, both Park's vector analysis and Fortescue transformation were applied, as demonstrated in [42], [43]. Refs. [44]-[46] investigated the use of acoustic signal analysis for fault diagnosis, utilizing non-invasive monitoring to identify a variety of defects.

A recent technique, which merges vibration and acoustic signals for fault diagnostics in INMs and other rotating machinery, has just been developed [47]. By converting signals into time-frequency spectra using an MI-CNN and the CQ-NSGT, this technique achieves excellent accuracy in fault detection under a variety of circumstances. Although it requires high sample rates and may be impacted by power supply variations. Ref. [48] concentrates on instantaneous power analysis, discovering deviations in power consumption patterns to detect defects. As shown in [49], [50], thermal imaging has been successfully applied to INM problem detection. Furthermore, [51] examined how image-based intelligent approaches have advanced condition monitoring (CM) and fault detection (FD) for instant messaging. Their analysis emphasizes the benefits of visualizing temperature distributions that may point to possible issues with the INM parts through the use of thermal imaging. Although these methods are dependent on environmental conditions and call for specialized equipment, they show the potential of thermal imaging for non-contact, real-time problem detection in instant messaging. In conclusion, SABTs provide several benefits, such as real-time applicability, non-invasive monitoring, and the capacity to identify a variety of defects. These techniques do have several drawbacks, though, namely their high computing demands, noise sensitivity, and requirement for specialist equipment.

AIBTs have been increasingly important in recent years as potent diagnostic tools for discovering and diagnosing problems in INMs [52], [53]. These techniques provide exceptional skills in precisely identifying and isolating flaws. AIBTs are essential for maintaining and keeping an eye on these vital INMs because they offer the requisite sophistication and precision [54]. Refs. [55]-[57] covered a variety of AIBTs and their efficacy in detecting various INM fault types, as well as recent developments in applying AIBTs for fault detection in INMs. A thorough analysis of the use of AIBTs for identifying stator problems in INMs was presented in [58]. Deep learning approaches were used in [59] to propose FD, which achieves high classification and localization accuracy for defects. Ref. [60] suggested using a robust method like ANN to identify and gauge the severity of problems; however, the model was intricate, and the outcomes were inconsistent. ANN demonstrated superior accuracy than other AI tools, such as K-nearest neighbors, Naïve Bayes, random forest, SVM, and decision tree, when estimating fault severity using attributes taken from the DWT of current signals [61]. Ref. [62] trained an MLP for estimating stator winding shorted turns using analytical and finite element models, showing efficacy with accuracy ranges between 88 and 99%. Ref. [63] employed RBFN and MLP to identify defects under unbalanced voltage with a 93–99% accuracy rate. Ref. [64] calculated an MLP-NN coefficient and achieved 99.6% fault detection accuracy. The DTC is a widely used control strategy for high-performance induction motor applications. Its fast dynamic response and high efficiency make it a strong candidate for fault-tolerant motor control. However, further research is needed to evaluate its performance under faulty operating conditions [65]. The objectives of this study are to:

- Evaluate the performance of DTC in the presence of RBFs.
- Assess the effectiveness of FFT, DWT, and STFT techniques in detecting and classifying RBFs.
- Discuss the advantages and limitations of integrating advanced signal processing methods with INM control strategies.

2. System Modeling

The three-phase, 1.1 kW squirrel-cage INM utilized in the simulations is described in Table 1. A system of differential equations, derived from Park's transformation and coupled circuit theory, can be used to numerically model a three-phase INM [66], [67]. The following assumptions are considered in the modeling process: (magnetic saturation is neglected, the magnetic field produced by the stator is assumed to be sinusoidal, iron losses are disregarded, and rotor bars are assumed to be electrically insulated. The stator and rotor voltage equations in the (d,q) reference frame are given as follows [68]-[70]:

$$[L]\frac{d[I]}{dt} = [V] - [R][I] \tag{1}$$

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where:

$$[L]=\begin{bmatrix} L_{SC} & 0 & -\frac{N_r}{2}M_{sr} & 0 & 0 \\ 0 & L_{sc} & 0 & -\frac{N_r}{2}M_{sr} & 0 \\ -\frac{3}{2}M_{sr} & 0 & L_{rc} & 0 & 0 \\ 0 & -\frac{3}{2}M_{sr} & 0 & L_{rc} & 0 \\ 0 & 0 & 0 & 0 & L_e \end{bmatrix} \tag{2}$$

$$[R]=\begin{bmatrix} R_S & -L_{sc}\omega & 0 & \frac{N_r}{2}M_{sr}\omega & 0 \\ L_{sc}\omega & R_s & -\frac{N_r}{2}M_{sr}\omega & 0 & 0 \\ 0 & 0 & R_r & 0 & 0 \\ 0 & 0 & 0 & R_r & 0 \\ 0 & 0 & 0 & 0 & R_e \end{bmatrix} \tag{3}$$

$$[V]=\begin{bmatrix} v_{ds} \\ v_{qs} \\ v_{dr} \\ v_{qr} \\ v_e \end{bmatrix} \tag{4}$$

$$[I]=\begin{bmatrix} i_{ds} \\ i_{qs} \\ i_{dr} \\ i_{qr} \\ i_e \end{bmatrix} \tag{5}$$

where the symbols $(i_{ds}, i_{qs}, i_{dr}, i_{qr})$ are the stator and rotor current components in the park reference frame, (R_s, R_r) represent the resistances of the rotor and stator, (L_s, L_r) are the stator and rotor inductances, and M_{sr} is the mutual inductance. The following equation provides the expression for electromagnetic torque [71], [72]:

$$T_e = \frac{3}{2}pN_rM_{sr}\left(I_{ds}.I_{qr} - I_{qs}.I_{dr}\right) \tag{6}$$

where P is the number of pole pairs.

This model enables an analytical approach to fault diagnosis and provides insight into how rotor bar issues affect motor dynamics. The DTC is a widely used control method for IMs due to its simplicity and fast dynamic response. DTC employs a predefined switching table to select the appropriate voltage vectors, enabling direct control of stator flux and electromagnetic torque [73], [74]. The following equations are used to estimate the stator flux and torque:

$$\psi_s = \int_0^t \left(V_s(\alpha,\beta) - R_s i_s(\alpha,\beta)\right).dt \tag{7}$$

$$T_e = \frac{3}{2}P\left(\psi_{s\alpha}i_{s\beta} - \psi_{s\beta}i_{s\alpha}\right) \tag{8}$$

where ψ_s is the stator flux, V_s is the stator voltage, R_s is the stator resistance, and T_e is the electromagnetic torque.

Table 1. Parameters of IM used in the simulation

Parameters	Value	Parameters	Value
P_n: output power (kW)	1.1 kW	L_e: inductance of end ring (H)	1e-7
V_s: stator voltage (V)	220 V	L_b: rotor bar inductance (H)	1e-7
P: pole number	1	L_{sf}: leakage inductance of stator (H)	0.0265
R_s: stator resistance (Ω)	7.58	N_s: number of turns per stator phase	160
R_r: rotor resistance (Ω)	6.3	Nr: number of rotor bars	16
R_b: rotor bar resistance Ω)	$150e^{-6}$	L: length of the rotor (m)	0.065
R_e: resistance of ring segment (Ω)	$150e^{-6}$	e: air-gap mean diameter (m)	0.0025
J: inertia moment (kg · m^2)	0.0054		

3. Implemented Techniques for Stator Current Analysis

Stator current analysis is among the most effective non-invasive techniques for diagnosing RBFs. Various signal processing methods offer distinct advantages in the detection and classification of these faults [75], [76].

3.1. FFT Technique

The FFT is a widely used frequency-domain technique for detecting RBFs in electrical machines [77], [78]. The RBFs generate characteristic sideband frequencies, which can be determined by the following relation:

$$f_{brb} = (1 \pm 2ks)f_s \tag{9}$$

where f_s is the supply frequency, and s is the slip.

3.2. DWT Technique

The DWT is highly effective for identifying transient and intermittent RBFs, as it enables time-frequency analysis [79], [80].

3.3. STFT Technique

The STFT is useful for tracking the evolution of RBFs over time, as it provides localized frequency analysis [81].

4. Simulation Results and Discussion

In this section, MATLAB/Simulink software is used to simulate the DTC that was previously covered in theory. Three steps make up the presentation of the simulation findings, which include a DTC comparison. The PI controller is used by both control methods to regulate speed, where these gains are obtained with Ziglar Nicolas. In a startup, the load is applied by $T_e = 3.5\ N.m$. Speed responses (rad/sec) for DTC shown in Fig. 1, Electromagnetic torque for DTC shown in Fig. 2, Stator current at startup and steady state for DTC shown in Fig. 3, Flux magnitude of a stator for DTC shown in Fig. 4, Flux circular trajectory (α, β) of the stator shown in Fig. 5, Speed reference reversing (157 rd/sec; - 157 rd/sec): rotor speed response for DTC shown in Fig. 6.

4.1. FFT Analysis

The FFT spectra of stator current are commonly used to detect broken RBFs in IMs. This part tries to analyze and compare some frequency contents. The characteristic frequencies can indicate the potential of broken RBFs. Fig. 7 is plotted in blue and likely represents a healthy IM and a faulty IM (BRB fault), which is in red.

Both spectra show a dominant peak at the fundamental frequency (probably at the supply frequency, f_s=28.35 Hz). In the healthy motor spectrum, the amplitude level is lower, and the harmonic components appear less pronounced. But in the faulty motor spectrum, additional peaks appear at characteristic fault frequencies, which may correspond to sideband frequencies due to BRB, according to this formula:

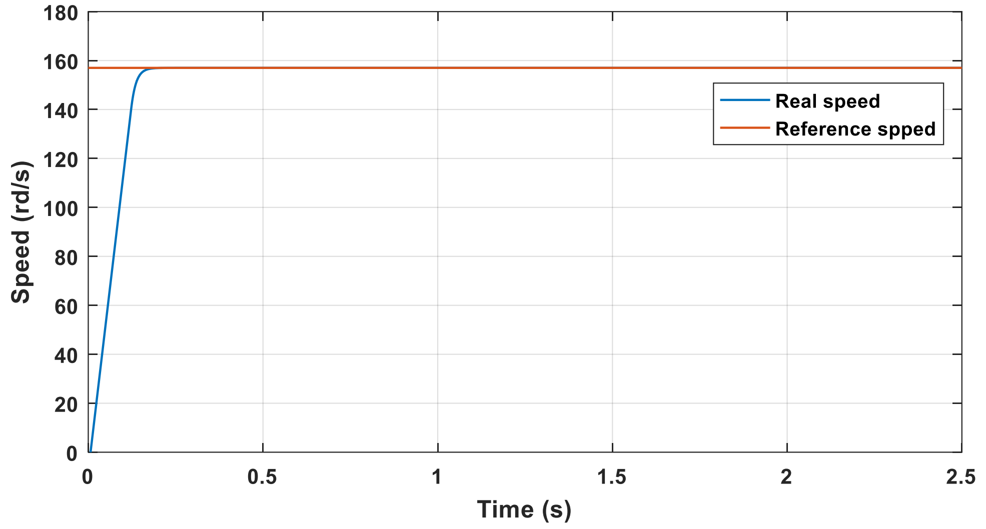


Fig. 1. Speed responses (rad/sec) for DTC

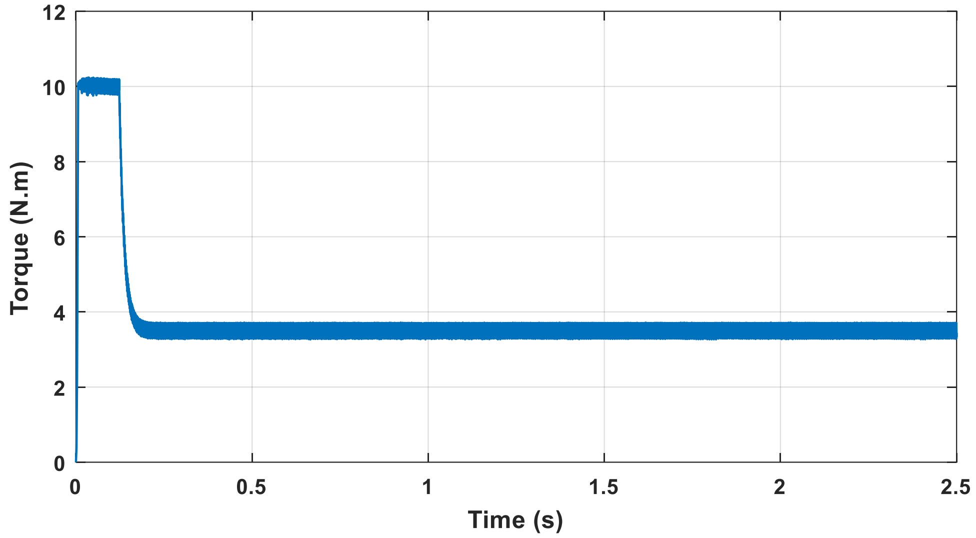


Fig. 2. Electromagnetic torque for DTC

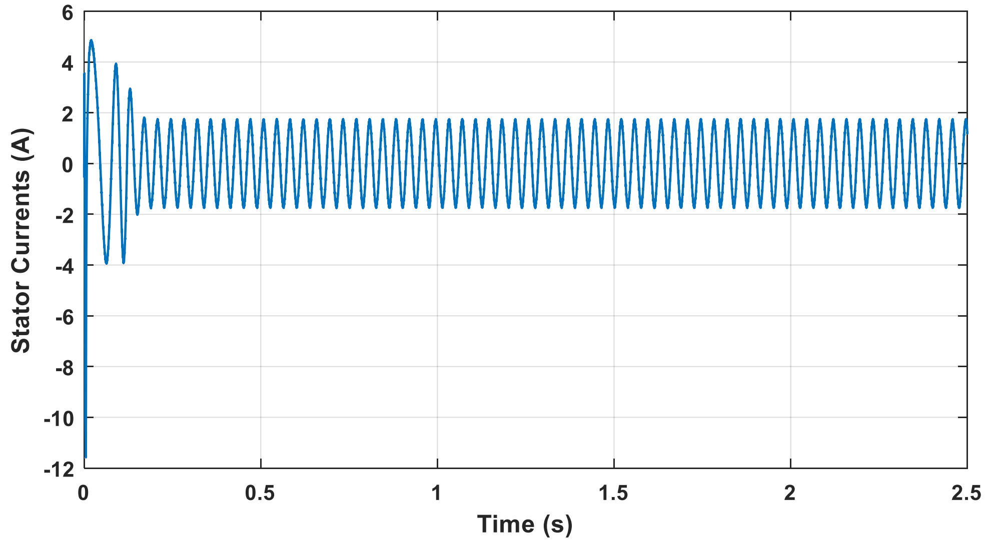


Fig. 3. Stator current at startup and steady state for DTC

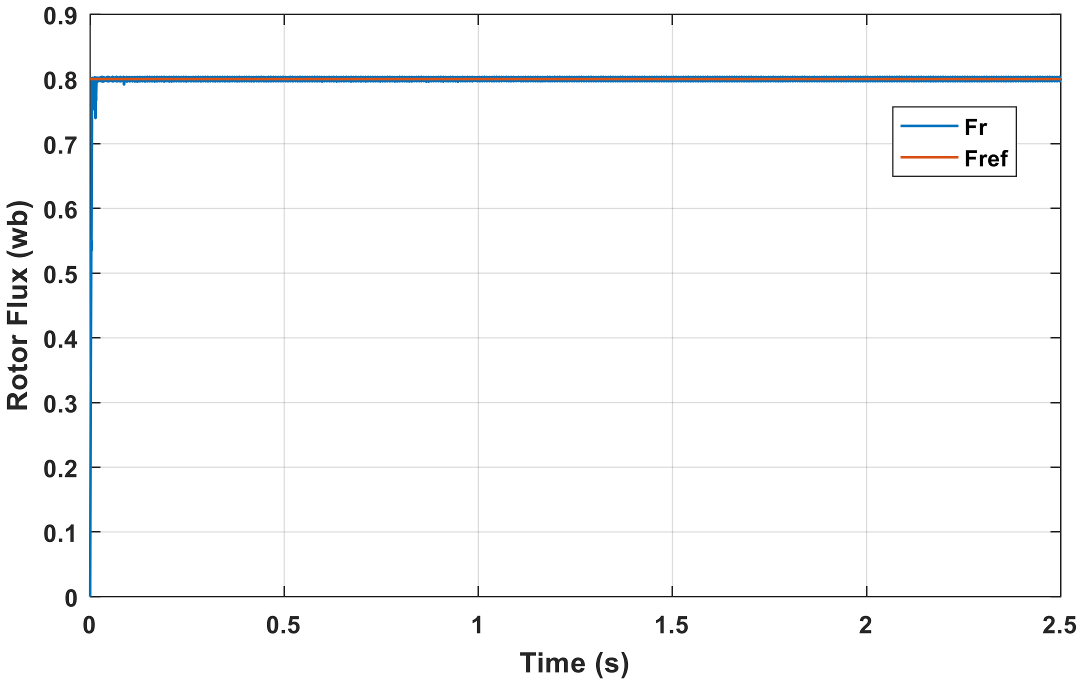


Fig. 4. Flux magnitude of a stator for DTC

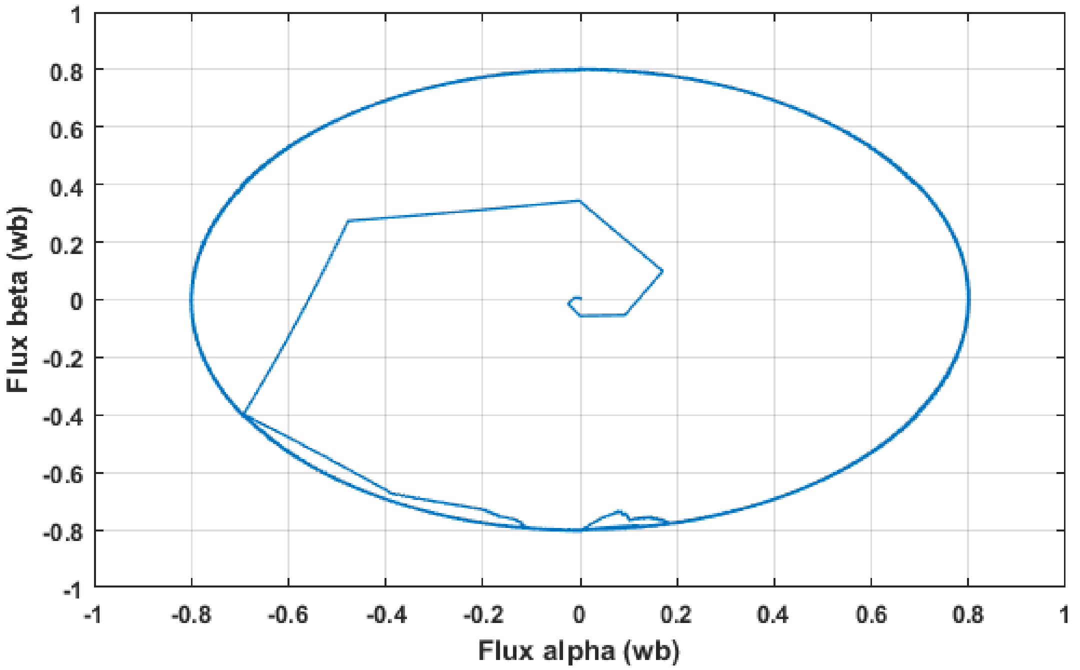


Fig. 5. Flux circular trajectory (α, β) of the stator

$$f_{BRB} = (1 \pm 2 * k * s)f_s \tag{10}$$

The faulty spectrum (red) exhibits higher noise levels and stronger harmonics, which could be an indicator of increased rotor asymmetry and instability. The healthy spectrum (blue) maintains a relatively stable noise floor, indicating a more balanced rotor operation. The faulty motor spectrum likely exhibits sideband components around the fundamental frequency and other harmonics as 139 Hz, 195 Hz, 307 Hz, 362 Hz, etc., due to the broken rotor bars, causing a BRB fault. The value of the additional sideband frequency is $2 * s * f_s = 5.992Hz$. Fig. 8 represents some sideband frequencies that indicate the presence of a BRB fault.

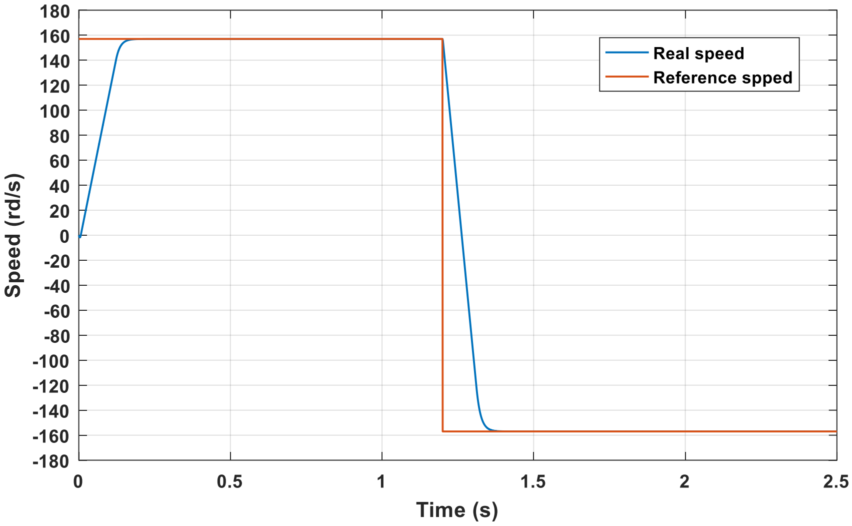
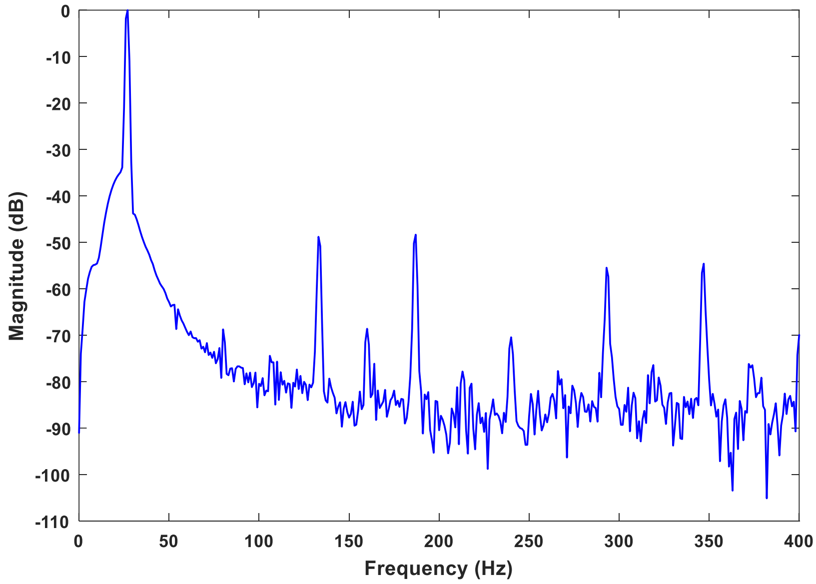
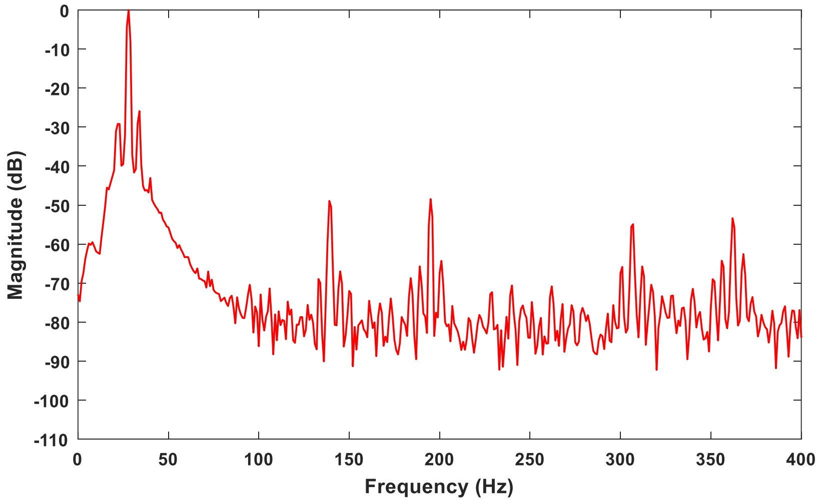


Fig. 6. Speed reference reversing (157 rd/sec; - 157 rd/sec): rotor speed response for DTC

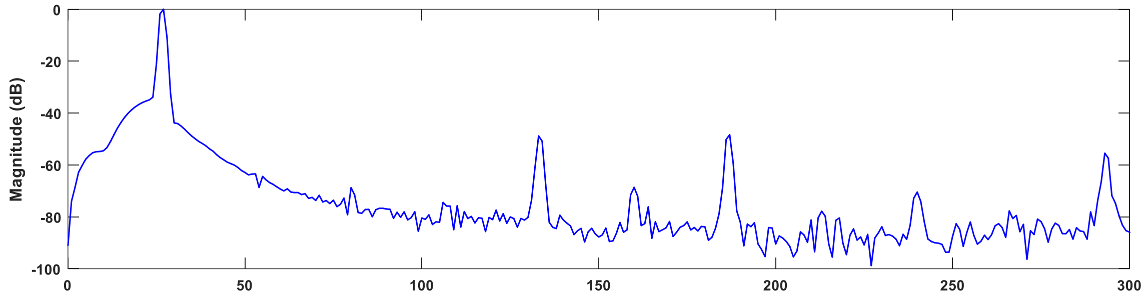


(a) Healthy IM

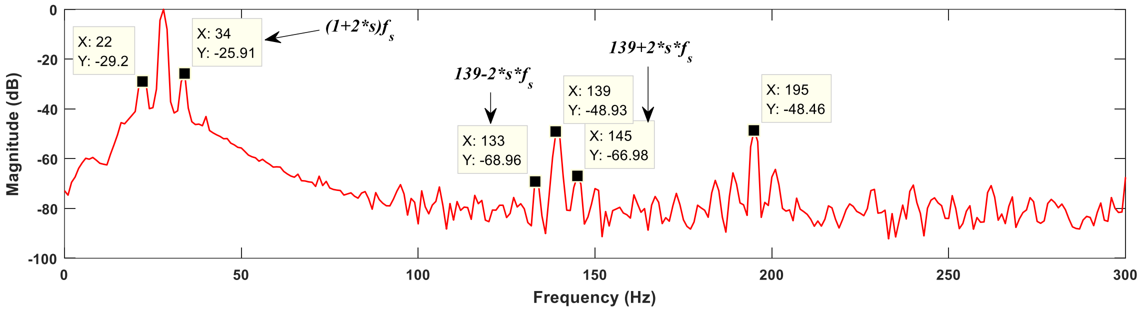


(b) Faulty IM

Fig. 7. Stator current spectra in healthy (blue) and fault (red) IM



(a) Healthy IM



(b) Faulty IM

Fig. 8. Sideband harmonic values from 0-300Hz

In addition, Table 2 shows clearly the new harmonic values of some sideband frequencies.

Table 2. Some additional harmonic values

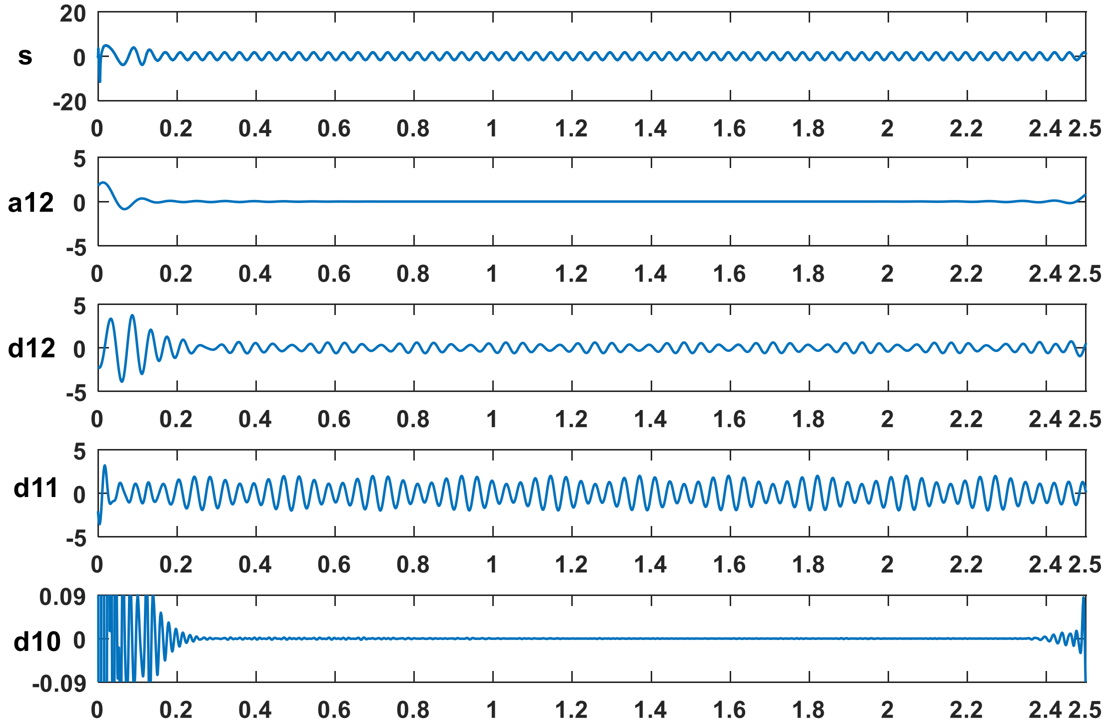
IM Frequency State of	Healthy IM	Faulty IM (BRB Fault)
Around 28 Hz	$f_{BRB}^{(+)} =/$	$f_{BRB}^{(+)} = 34\ Hz$
	$f_{BRB}^{(-)} =/$	$f_{BRB}^{(-)} = 22\ Hz$
Around 139 Hz	$f_{BRB}^{(+)} =/$	$f_{BRB}^{(+)} = 145\ Hz$
	$f_{BRB}^{(-)} =/$	$f_{BRB}^{(-)} = 133\ Hz$
Around 195 Hz	$f_{BRB}^{(+)} =/$	$f_{BRB}^{(+)} = 201 Hz$
	$f_{BRB}^{(-)} =/$	$f_{BRB}^{(+)} = 189\ Hz$

The comparison between spectra suggests that the presence of additional frequency components and higher noise levels in the faulty motor spectrum is a key indicator of a rotor fault. This type of analysis is crucial in predictive maintenance to detect broken rotor bars at an early stage before severe degradation occurs.

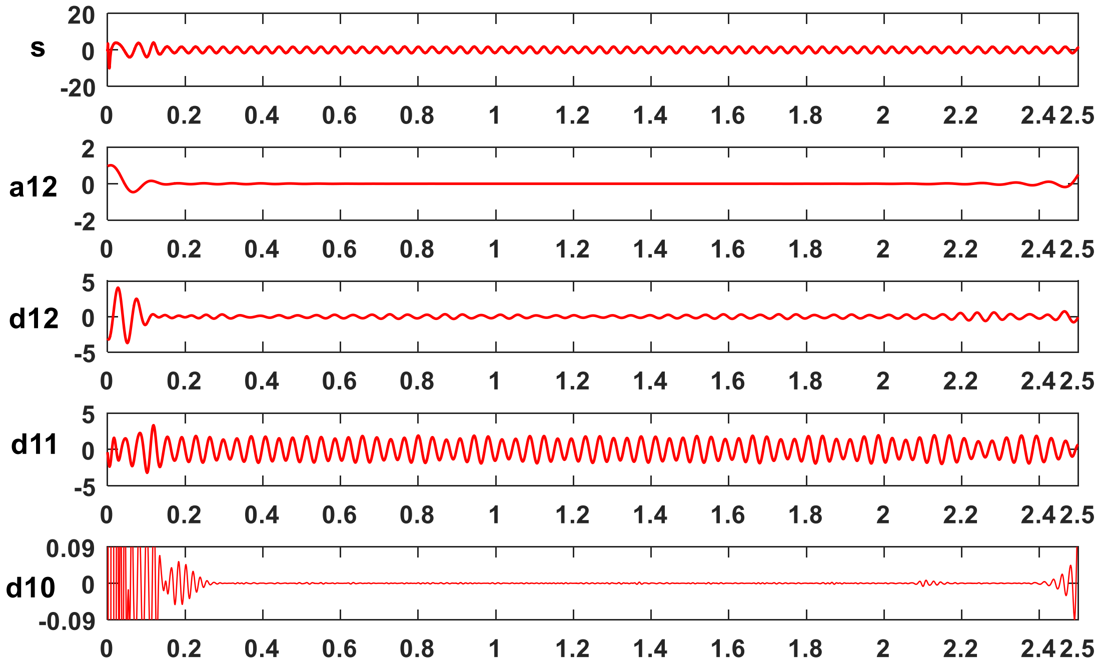
4.2. DWT Analysis

This part uses DWT decompositions to analyze the stator current signal. Based on the comparison of DWT results in healthy motor (blue) and a faulty motor (red) can be a good decision about the IM state. Both figures show multi-level wavelet decompositions to detect BRB faults. We can see clearly that the signal components are more uniform and exhibit smooth variations in the healthy state of IM. But in a faulty state, the differences in the lower-level components (high-frequency bands) show more abrupt variations. This is due to increased noise or abrupt energy changes under faults and broken rotor bars.

The faulty IM exhibits higher energy in high-frequency components, indicating the presence of a BRB fault. Precisely, this variation is clear in d10. The DWT analysis complements the FFT by highlighting transient behaviors that spectral methods might overlook. The faulty motor exhibits clear disturbances at different decomposition levels, suggesting wavelet-based fault detection is an effective method. DWT analysis of the stator current (healthy and faulty IM) shown in Fig. 9.



(a) Healthy IM



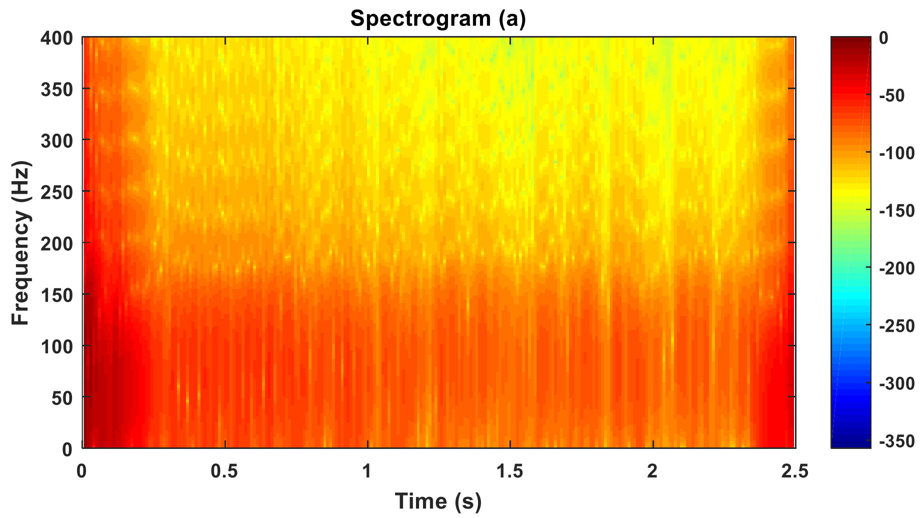
(b) Faulty IM

Fig. 9. DWT analysis of the stator current (healthy and faulty IM)

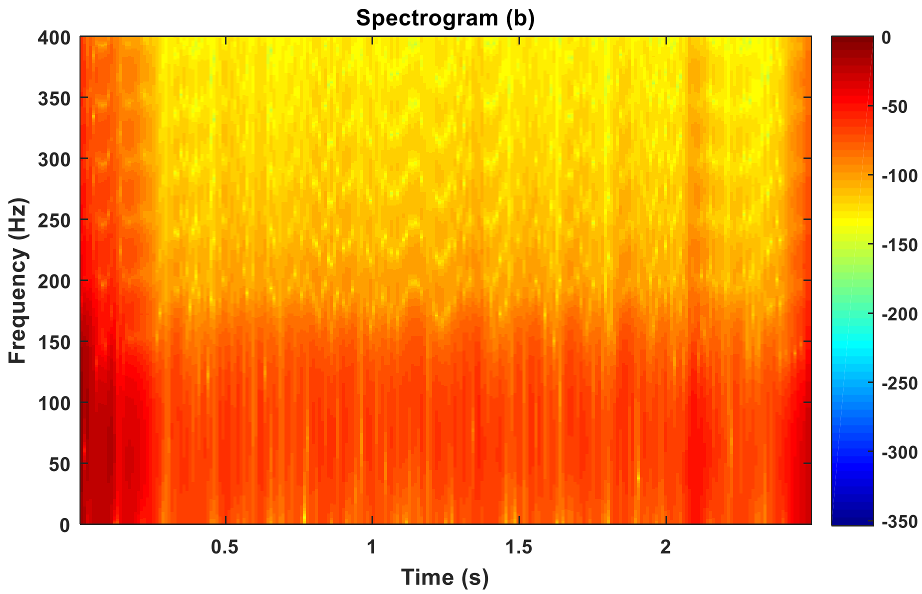
4.3. STFT Analysis

To exploit the information in d10, we try to analyze this signal carefully based on the STFT tool. The STFT is a technique used to analyze how the frequency content of a signal changes over time. Unlike the FFT, which provides a global frequency analysis, the STFT allows tracking frequency variations over time, making it ideal for detecting intermittent or evolving faults. We can define some spectrogram interpretations as follows: (X-axis (horizontal): Time (s), Y-axis (vertical): Frequency (Hz), Color Scale: Signal amplitude in dB, Red: High energy (high signal amplitude), Blue: Low energy (low signal amplitude).

So, in healthy cases, the energy is mainly concentrated around specific frequency bands, likely around the fundamental frequency (28.35 Hz) and its harmonics (see Fig. 10). The time evolution is relatively stable, with no significant fluctuations or sudden appearance of new components. There is some dispersion in higher frequencies, which is normal for a healthy motor. But in the faulty case (Fig. 10), it's clear that the energy is increased in multiple frequency bands, especially in the high-frequency range. Additional modulations and intensity variations indicate disturbances caused by a BRB fault. Unlike the healthy motor, intermittent frequency components appear in the high-frequency range, which is characteristic of broken rotor bar faults. Low-frequency components are also affected, meaning the fault impacts not only high frequencies but also the overall motor performance. Finally, the healthy motor spectrogram is relatively homogeneous with stable frequency components. The faulty motor exhibits irregularities in frequency bands and increased high-frequency energy, indicating possible issues under a broken rotor bar fault.



(a) Healthy IM



(b) Faulty IM

Fig. 10. STFT of d10 under two conditions for (a) Healthy IM and (b) Faulty IM

5. Conclusions

RBFs can severely impact IM performance, leading to decreased efficiency, elevated vibrations, and even IM failure. Signal analysis is a powerful tool for monitoring IMs. A thorough analysis of identifying these defects using sophisticated signal processing techniques has been presented in this research. To assess the robustness of DTC, the behavior of the IM has been examined in both normal and abnormal conditions. FFTs show the impact of a fault on characteristic frequencies. However, DWTs reveal distortions in the signal's temporal structure. A hybrid approach combining FFT and DWT improves the early detection of BRB faults. In addition, STFT also allows a good visualization of frequency variations over time, which is a significant advantage over traditional FFT analysis. Therefore, STFT was effective in detecting gradual variations over time. This paper attempted to track fault evolution over time using three different techniques. STFT detects specific modulations caused by rotor or stator faults. This work also used and combined FFT and DWT to provide a comprehensive analysis dedicated to detecting broken RBFs. Although the system analyzed the signals in the presence of the DTC command, the results clearly distinguished between the different conditions. Our perspective will exploit other techniques and faults to make a good decision about the state of the IM.

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Data Availability: The data used to support the findings of this study are available at reasonable request from the corresponding author.

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