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Rotor Bar Fault Diagnosis in Indirect Field–Oriented Control-Fed Induction Motor Drive Using Hilbert Transform, Discrete Wavelet Transform, and Energy Eigenvalue Computation

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Abstract: The most powerful technology in the condition-based maintenance (CBM) framework for rotating machinery is fault detection (FD) and fault diagnosis (FDS). This paper investigates the broken rotor bar (BRB) FDS utilizing Hilbert transform (HT), discrete wavelet transform (DWT), and energy eigenvalue (EEV) computation with the induction motor (IM) drive handled by the indirect field orientation control (IFOC). The stator current spectrum, which the HT collects, is utilized to determine BRB degradation. The DWT decomposes the signal while the fast Fourier transform (FFT) recovers the signal's frequency and amplitude factors. The EEV of the motor current in the signal determines the degree of the malfunction and provides a better method for recognizing errors. The DWT is used to overcome the Fourier analysis's drawbacks and is primarily dedicated to non-stationary signals. While DWT is used, the malfunctioning BRB's stator current signal is restrained from its original amplitude. The results demonstrate that the proposed method can identify and diagnose faults in an IM drive even under different loads.

Keywords: discrete wavelet transform; Hilbert transform; indirect field-oriented control; energy eigenvalue



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1. Introduction

Because of its strong design, small size, adaptability to regulate, and readily available power supply, the three-phase induction motor (IM) is widely used in various industrial sectors, including aerospace, chemicals, atomic energy, automobiles, and the food industry. Nevertheless, these motors can be impacted by various conditions that reduce their performance, such as humidity, temperature, dirt, and overload. Any malfunction in the induction motor reduces its performance, ultimately affecting how well it works [1]. Additionally, the industrial process is suspended, production is reduced, and the prevalence of failures impacts other related devices. Consequently, the need for a suitable fault condition monitoring (CM) system becomes critical to identify the prediction and optimization, reliability enhancement, and downtime reduction. For these factors, an expensive expenditure is necessary, one that depends on the motor's reliability and financial capacity [2].

Mechanical defects and electrical faults are the two main categories of IM damages. BRB, unbalanced voltage, inter-turns failure, overloading, and under- or over-voltage are the electrical defects that occur most commonly. Mechanical faults, like bearing issues, eccentricity, and mass imbalance, may damage an IM [3,4]. Several detection methods are used to establish the CM of the motor. Until now, several evaluations have been developed to analyze induction motors' capabilities, dependability, and flaws [5]. Two articles [6,7] reported on the statistical analysis of the IEEE (Institute of Electrical and

Electronics Engineers) and the defect examination by the EPRI (Electric Power Research Institute) on IM problems.

The majority of IM failures, per their assessment, are depicted in Figure 1. Investigations on different IM defects confirm that rotor failures are one of the machine defects that may occur. By employing various detecting techniques, the study of input characteristics, including flux, temperature, and vibration, can be used to monitor an induction motor's state of operation and identify BRB failure. A technique to extract this undetected incipient defect must be provided to solve this issue. An incipient breakdown at a single bar does not cause any obvious damage symptoms aside from the potential for quick, deadly effects [8]. Early detection of rotor breakdowns can prevent subsequent faults like stator winding degradation. Therefore, it is advantageous to identify these issues at their earliest stage to prevent further harm to the IM and shorten outages [9].

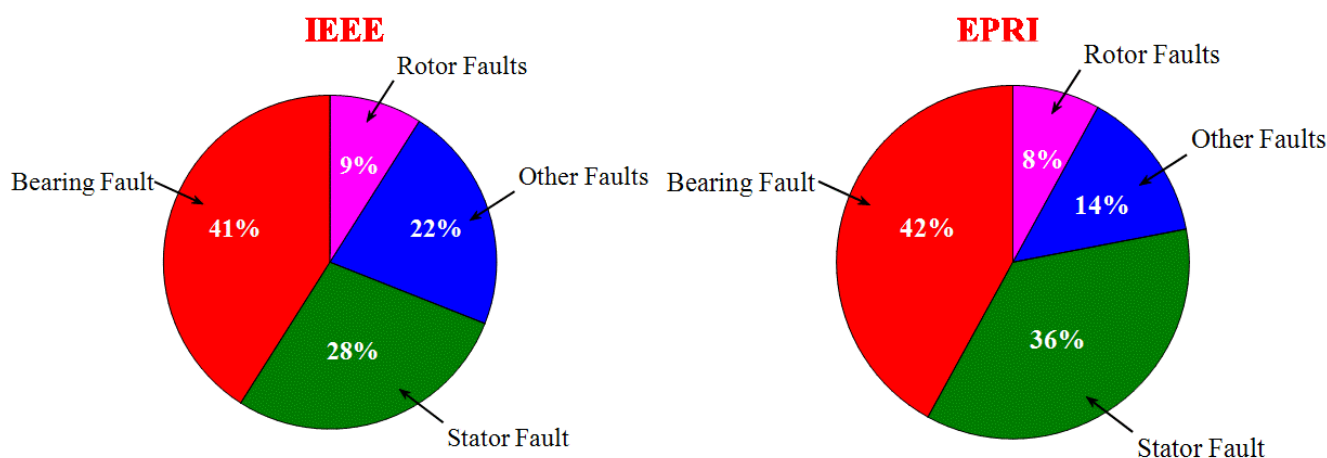


Figure 1. Failure percentage of IM.

Vector-oriented drives need to function at low speeds in most industrial applications. Because of its simple structure and model, the IFOC constitutes one of the prevalent controls in the vector control of IMs. The IFOC provides effective dynamic torque control that enables quick reaction to step variations in load torque. Additionally, the IFOC removes the controller's reliance on temperature accuracy [10].

The FD and FDS have recently gained prominence as computing power has increased using artificial neural networks (ANNs), machine learning, deep learning, and signal processing approaches [11]. A health monitoring system for manufacturing robots using artificial intelligence is presented in [12]. Using a current vector structure, the rising diameter and trajectory displacement are indicators for predicting the presence of magnetic saturation and broken rotor bars [13]. In this paper, the authors used multiple signal processing tools for quick FDS.

Motor current signature analysis (MCSA) is frequently employed for IM fault diagnosis and monitoring. Each sort of fault categorization is understood using its spectrum characteristic. The sideband elements of the current spectrum are extracted and examined to demonstrate rotor flaws. A method to identify BRB frequencies from the spectrum in IMs using the MCSA approach was shown in [14]. The experimental and simulation findings of rotor bars that had deteriorated were reviewed. These findings demonstrated that the technique employed for the spectrum of the current research is sufficient for identifying rotor bar defects early on. A novel approach using the wireless sensor was proposed in [15] to identify the BRB failure. The findings of this approach were discovered and reviewed. The results showed several benefits over conventional methodologies in accurately differentiating healthy and defective IMs and determining the seriousness of faults, especially with a no-load condition. Support vector machine (SVM)-based failure classification techniques were discussed in [16]. Numerous induction defects were investigated, including a BRB, an imbalanced phase fault, and an imbalanced rotor.

FFT analysis is an effective method for locating BRB defects when an IM operates in a steady-state environment, such as with a stable frequency supply [17]. Nevertheless, the time-domain need impacts the FFT's effectiveness and accuracy. Hence, advanced signal processing techniques, including DWT [18], HT [19] and short-time Fourier transform (STFT) [20], are used to address the FFT problems. A novel strategy was proposed in [21] based on observing a few statistical characteristics discovered by examining the initial stator current envelope. Experiments in the electrical laboratory were used to test and validate the proposed HT approach. Reference [22] presented a novel strategy as a probabilistic tool for IM BRB defect diagnosis. This method could recognize and distinguish between half and single bars. In [23], authors proposed multiple signal classification (MUSIC) techniques to make it easier to recognize impending bar ruptures for early diagnosis.

The use of ANNs for BRB fault detection was described in [24]. The development of fault diagnostics for IM employing both Wavelet and HT was discussed in [25]. A genetic algorithm was used to identify the fault frequencies that could effectively categorize a range of concerns even in background noise [26]. The work mentioned above was completed in an open-loop IM drive. However, FDS in open-loop drives is insufficient when the IM control framework is complicated.

A report on direct torque control (DTC)-fed IM drive-fault diagnostics utilizing the FFT tool can be found in [27]. The diagnosis of the BRB fault in the IFOC that supplied the IMD through the DWT was addressed in [28]. But, when using DWT, it is necessary to have more phase information and better directionality. Hence, multiple signal processing methods, including HT, FFT, and DWT, are used for BRB fault identification in IFOC-based IM drives, as proposed in this paper. Also, the fault intensity is then computed using the EEV method. The process tests the drive's dynamic responsiveness and identifies the machine's healthy and defective states. Figure 2 depicts the proposed system's comprehensive block diagram. Both simulation and real time are used to evaluate the proposed system.

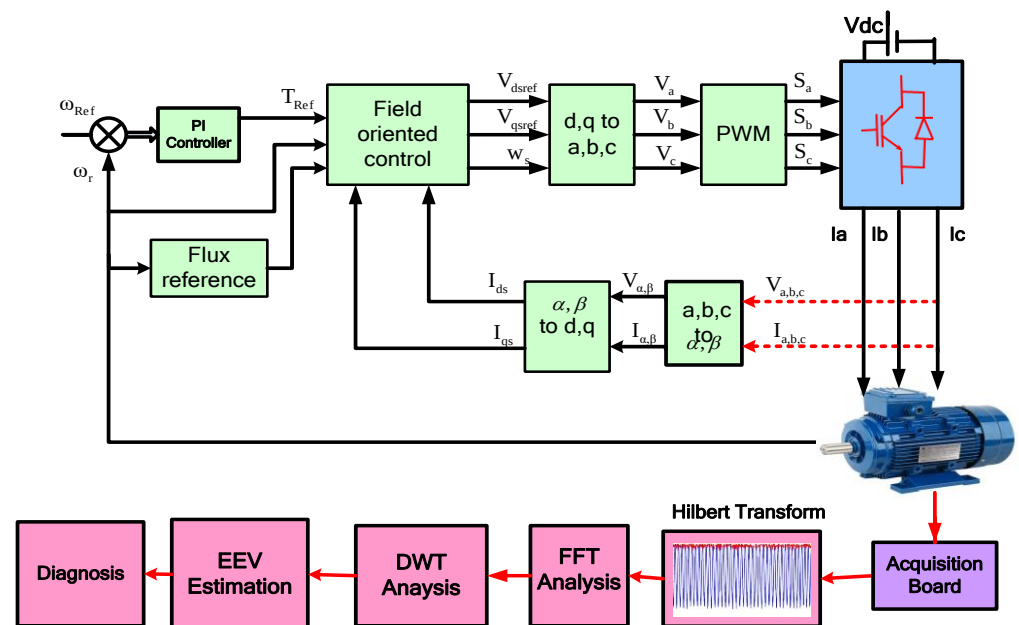


Figure 2. Proposed block diagram for FDS in IFOC-fed drive.

This paper is structured as follows: The IM model concerning BRB failure is discussed in Section 2. The IFOC-fed drive and simplified IM model are illustrated in Section 3. The fault diagnosis using HT and DWT is covered in Section 4. The FDS is provided together with a discussion in Section 5. The proposed work is compared with previous works in Section 6. The conclusion of the proposed work is illustrated in Section 7.

2. Modeling of IM with BRBs

The modified rotor model was constructed to assess the impact of the BRB fault [29]. This model illustrates the rotor's shape, and Figure 3 shows its equivalent circuit. The rotor's reference frame, which may be stated using the canonical form, is selected to provide a simplified model [30].

$$[L_a] \frac{d[I_m]}{dt} = [V_a] - [Z_a][I_a] \quad (1)$$

where

$$[L_a] = \begin{bmatrix} L_{sc} & 0 & \frac{-N_r M_{st}}{2} & 0 \\ 0 & L_{sc} & 0 & \frac{-N_r M_{st}}{2} \\ \frac{-3}{2} M_{st} & 0 & L_{sc} & 0 \\ 0 & \frac{-3}{2} M_{st} & 0 & L_{sc} \\ 0 & 0 & 0 & L_{sc} \end{bmatrix}$$

$$[Z_a] = \begin{bmatrix} R_s & -\omega_r L_{sc} & 0 & \frac{N_r \omega_r M_{st}}{2} & 0 \\ -\omega_r L_{sc} & R_s & \frac{-N_r \omega_r M_{st}}{2} & 0 & 0 \\ 0 & 0 & R_r & 0 & 0 \\ 0 & 0 & 0 & R_r & 0 \\ 0 & 0 & 0 & 0 & R_e \end{bmatrix}$$

$$[I_a] = \begin{bmatrix} i_{ds} \\ i_{qs} \\ i_{dr} \\ i_{qr} \\ i_{ei} \end{bmatrix}, [V] = \begin{bmatrix} V_{ds} \\ V_{qs} \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

where L_a is the inductance matrix, I_a is the motor current matrix, Z_a is the impedance matrix, and V is the voltage matrix. V_{ds} and V_{qs} are stator voltages with respect to the d and q axes, respectively; i_{ds} and i_{dr} are stator and rotor currents, respectively, with respect to the d axis; i_{qs} and i_{qr} are stator and rotor currents, respectively, with respect to the q axis; ω_r is the rotor's angular speed; R_s and R_r are stator and rotor winding resistances, respectively; and M_{st} is the mutual inductance between stator and rotor.

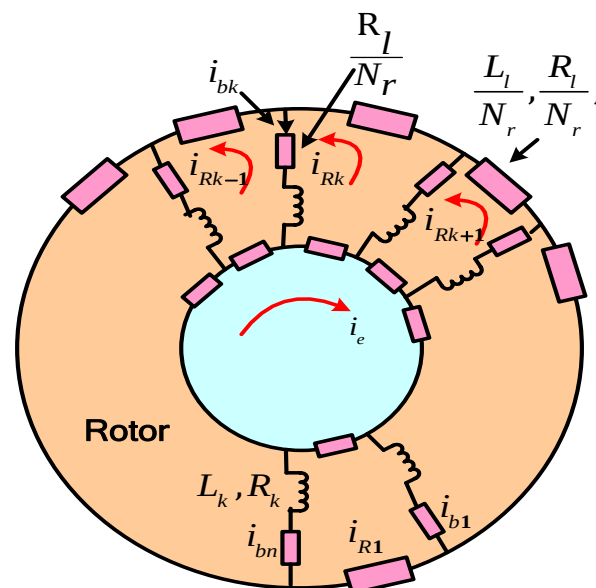


Figure 3. Equivalent circuit of rotor cage.

The cyclic inductances L_{cb} and rotor resistance R_r are given as [9]

$$L_{cb} = L_{ab} = M_{rr} + 2\frac{L_k}{N_r} + 2L_k(1 - \cos \alpha) \quad (2)$$

$$R_r = 2\frac{R_k}{N_r} + 2R_l(1 - \cos \alpha) \quad (3)$$

where α is the electric angle, N_r is the number of rotor bars, M_{rr} is the mutual inductance of rotor meshes, and L_k is the specific rotor inductance.

The rotor loop's real inductance (L_{ab}) is written as

$$L_{ab} = \left(\frac{N_r - 1}{N_r^2} \right) \frac{\mu_0}{e} 2\pi r l \quad (4)$$

where r and e are the airgap mean radius and thickness, respectively; l is the magnetic circuit length, and μ_0 is the permeability of magnetic air.

The mutual inductance of rotor meshes (M_{rr}) is given by

$$M_{rr} = \frac{-1}{N_r^2} \frac{\mu_0}{e} 2\pi r l \quad (5)$$

The stator's total cyclic inductance (L_{sb}) is denoted by

$$L_{sb} = L_m + L_{sf} \quad (6)$$

where L_{sf} is the leakage inductance of the stator.

The magnetizing inductance (L_m) is given by

$$L_m = 4\mu_0 \frac{N_s^2 \cdot r \cdot l}{e \cdot p^2 \Pi} \quad (7)$$

where N_s is the stator turns per phase and p is the number of pole pairs.

The mutual inductance (M_{sr}) is given by

$$M_{sr} = \left(\frac{4}{\Pi} \right) \left(\frac{\mu_0}{e \cdot p^2} \right) N_s \cdot r \cdot l \sin \frac{a}{2} \quad (8)$$

The resistance matrix must be adjusted in the case of a rotor fault. The fault matrix is represented as

$$[R_{bf}] = [R_r] + \begin{bmatrix} 0 & \dots & 0 & 0 & 0 & \dots \\ \vdots & \dots & \vdots & \vdots & \vdots & \dots \\ 0 & \dots & 0 & 0 & 0 & \dots \\ \vdots & \dots & R'_{bk} & -R'_{bk} & 0 & \dots \\ 0 & \dots & -R'_{bk} & R'_{bk} & 0 & \dots \\ 0 & \dots & 0 & 0 & 0 & \dots \\ \vdots & \vdots & \vdots & \vdots & 0 & \dots \end{bmatrix} \quad (9)$$

The rotor fault matrix relates to the extended park transition matrix. The simplified fault matrix is created after the simplification method.

$$[R_{bfdq}] = \begin{bmatrix} R_{bdd} & R_{bdq} \\ R_{bqd} & R_{bqq} \end{bmatrix} \quad (10)$$

The four terms for the BRB fault resistances are represented as follows [27,31]:

$$\begin{cases} R_{bdd,bqq} = R_r + \frac{2}{N_r}(1 - \cos \alpha) \sum_k R_{bfk}(1 \pm \cos(2k - 1) \cdot \alpha) \\ R_{bdq,bqd} = -\frac{2}{N_r}(1 - \cos \alpha) \sum_k R_{bfk} \cdot \sin(2k - 1) \cdot \alpha \end{cases} \quad (11)$$

where R_{bfk} is the BRB resistance and $K = 1, 2 \dots N_r$. The summation of the above-mentioned equation can be employed to assign a fault condition to all rotor bars. In R_{bk} , this is accomplished by increasing the index of k from the primary value of the resistance. Also, the broken bar is characterized by the index ' K '.

3. IFOC-Based Drive under Rotor Failure

The stator current in the space vector's two components is separated using the IFOC approach. The stator current phasor can be defined as the total phasor current of the direct axis and quadrature stator currents in any reference frame [2].

$$I_{st} = \sqrt{(i_{qs}^e)^2 + (i_{ds}^e)^2} \quad (12)$$

The current relationship of two phases to three phases is given by

$$\begin{bmatrix} i_{qs}^e \\ i_{ds}^e \end{bmatrix} = \frac{2}{3} \begin{bmatrix} \cos \theta_f & \cos(\theta_f - \frac{2\pi}{3}) & \cos(\theta_f + \frac{2\pi}{3}) \\ \sin \theta_f & \sin(\theta_f - \frac{2\pi}{3}) & \sin(\theta_f + \frac{2\pi}{3}) \end{bmatrix} \begin{bmatrix} i_{as} \\ i_{bs} \\ i_{cs} \end{bmatrix} \quad (13)$$

The co-sinusoidal electrical angle elements that make up the matrix are present. Adding slip and rotor angle makes calculating the electric field angle possible.

$$\theta_f = \theta_{sl} + \theta_r \quad (14)$$

The slip angle (θ_{sl}) can be calculated by integrating the slip speed and using the formula,

$$\theta_{sl} = \int \omega_{sl} \quad (15)$$

The IFOC was derived from the derivations above, and it was given requests for flux and torque and orders for slip angle and stator current phasor components. The command values i_T^* , i_f^* , and ω_{sl}^* are expressed as [32]

$$i_T^* = \frac{T_{em}^*}{K_{et}\phi_r^*} = \left(\frac{2}{3}\right) \left(\frac{2}{P}\right) \frac{T_{em}^*}{\phi_r^*} \frac{L_r}{L_m} \quad (16)$$

$$i_f^* = (1 + p \frac{L_r}{R_r}) \frac{\phi_r^*}{L_m} \quad (17)$$

$$\omega_{sl}^* = \frac{R_r L_m}{L_T} \frac{i_T^*}{\phi_r^*} \quad (18)$$

Figure 4 shows the block diagram of the IFOC-fed IMD. The command of torque (i_T^*) is a component of the speed error signal that the PI controller commonly retrieves. Directly issuing the flux command (i_f^*) is feasible. The rotor's position is then determined using encoders and converted into comparable digital data for feedback control.

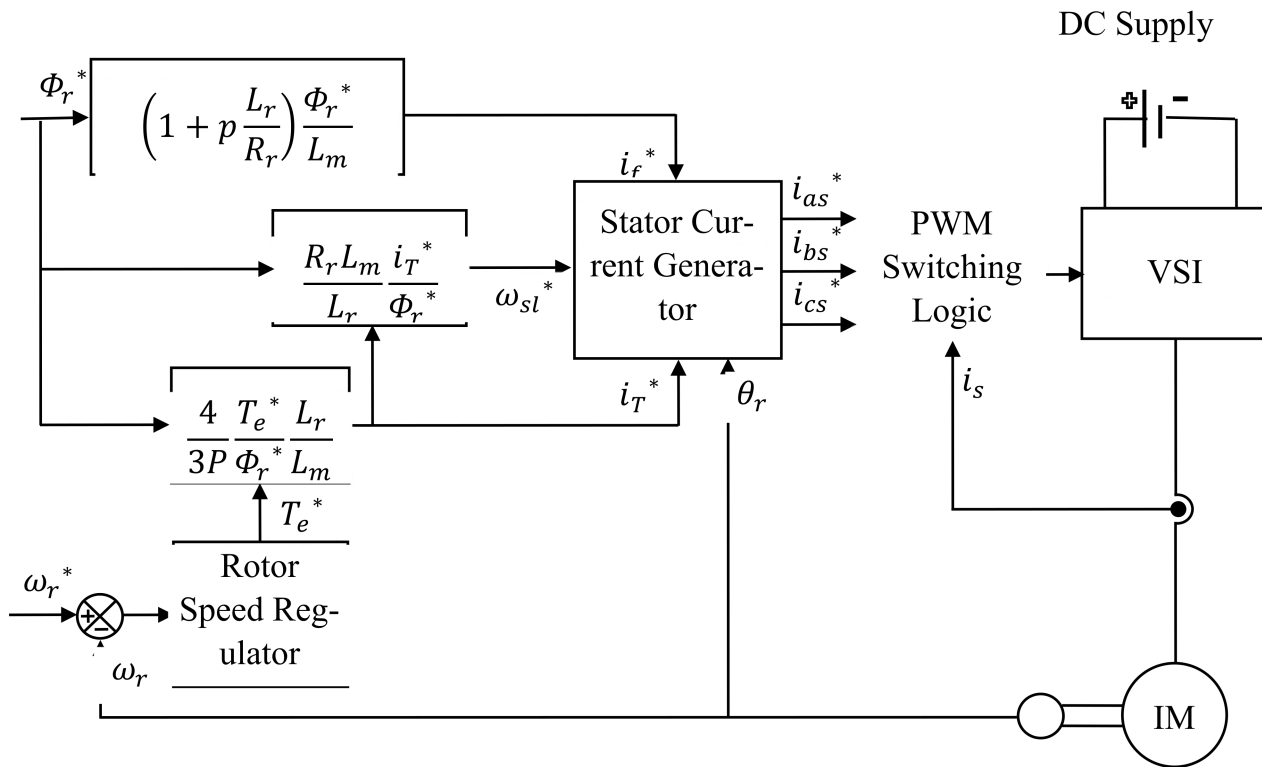


Figure 4. Block diagram of IFOC-fed IM drive.

The IFOC-fed drive's electromagnetic torque can be represented as [33]

$$T_{em} = -\frac{3}{4}p \frac{N_r \cdot M_{sr}}{L_{rc}} (\psi_{dr} i_{qs} - \psi_{qr} i_{ds}) \quad (19)$$

When the previous formula is modified to include a quadratic flux component of zero, the electromagnetic torque can be expressed as

$$T_{em} = -\frac{3}{4}p \frac{N_r \cdot M_{sr}}{L_{rc}} \psi_{dr} i_{qs} = K_1 \cdot \psi_{dr} i_{qs} \quad (20)$$

where

$$K_1 = -\frac{3}{4}p \frac{N_r \cdot M_{sr}}{L_{rc}}$$

The components of the stator and rotor flux are listed in Equation (21).

$$\begin{cases} \psi_{ds} = L_{sc} \cdot i_{ds} - \frac{N_r}{2} M_{sr} \cdot i_{dr} \\ \psi_{qs} = L_{sc} \cdot i_{qs} - \frac{N_r}{2} M_{sr} \cdot i_{qr} \\ \psi_{dr} = -\frac{3}{2} M_{sr} \cdot i_{ds} + L_{rc} \cdot i_{dr} \\ \psi_{qr} = -\frac{3}{2} M_{sr} \cdot i_{qs} + L_{rc} \cdot i_{qr} \end{cases} \quad (21)$$

When the field orientation is applied, the d–q current elements become

$$\begin{cases} i_{ds} = -\frac{2}{3} \left(\frac{\psi_{dr} (1 + T_r \cdot s)}{M_{sr}} \right) \\ i_{qs} = \frac{T_e}{K_1 \cdot \psi_{dr}} \end{cases} \quad (22)$$

Also, the slip frequency (f_{sl}) can be written as

$$f_{sl} = (1 \pm 2ns) f_s \quad (23)$$

where f_s is the supply frequency, s is slip, and n is an integer ($n = 1, 2, 3 \dots$).

The system equation with state models is expressed by the following equation [34]:

$$\begin{cases} \dot{X}(t) = AX(t) + BU(t) \\ Y(t) = CX(t) \end{cases} \quad (24)$$

$$X^T = [i_{ds} \quad i_{qs} \quad \psi_{dr} \quad \psi_{qr} \quad i_e]; u^T = [V_{ds} \quad V_{qs}]; y^T = [i_{ds} \quad i_{qs}]$$

where i_e is the ring current.

$$A = \begin{bmatrix} -k_1 - k_2 R_{bdd} & \omega_r - k_2 R_{bdq} & -k_3 R_{bdd} & -k_4 \omega_r - k_3 R_{bdd} & 0 \\ -\omega_r - k_2 R_{bdq} & -a_1 - k_2 R_{bdd} & -k_4 \omega_r - k_3 R_{bdq} & -k_3 R_{bqq} & 0 \\ -k_5 R_{rdd} & -k_5 R_{rdq} & -k_6 R_{bdd} & 0 & 0 \\ -k_5 R_{rqd} & -k_5 R_{rqq} & -k_6 R_{bdq} & -k_6 R_{bqq} & 0 \\ 0 & 0 & 0 & 0 & -k_7 \end{bmatrix}$$

$$B = \begin{bmatrix} k_8 & 0 & 0 & 0 & 0 \\ 0 & k_8 & 0 & 0 & 0 \end{bmatrix}^T; C = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

$$k_1 = \frac{R_1}{\sigma L_{sb}}; k_2 = \frac{3M_{sr}^2 \cdot N_r}{4L_{sb}L_{cb}^2 \sigma}; k_3 = \frac{M_{sr} \cdot N_r}{2L_{sb}L_{cb}^2 \sigma}; k_4 = \frac{M_{sr} \cdot N_r}{2L_{sb}L_{cb} \sigma}$$

$$k_5 = \frac{3M_{sr}}{2L_{sb}}; k_6 = \frac{1}{L_{cb}}; k_7 = \frac{R_l}{L_l}; k_8 = \frac{1}{\sigma L_{sb}}; \text{and } \sigma = 1 - \left(\frac{3M_{sr}^2 \cdot N_r}{4L_{sb}L_{cb}} \right)$$

4. Fault Diagnosis Process

Figure 5 shows the proposed fault diagnostic approach through flowchart representation. The closed-loop IFOC-fed drive was initially created to test the machine's performance in both healthy and broken states. Separate the envelope signal to obtain the analytical signal of $x(t)$ using HT. The frequency parameters are then calculated using FFT. Then, utilizing DWT, decompose the envelope signal obtained from HT. Finally, the fault severity is determined based on the stator current's EEV.

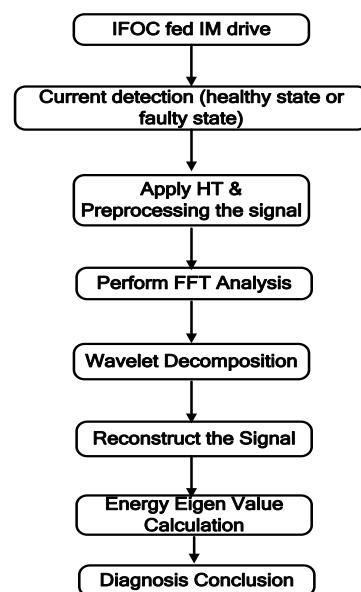


Figure 5. Flowchart for diagnosis process.

4.1. HT

HT is a technique for processing time–frequency signals with high precision and convergence. Additionally, it is a non-linear and non-stationary adaptive technique [35].

Therefore, HT is one of the most popular signal analysis techniques used in defect identification nowadays. The output of HT is not the same as the original signal; rather, it is an entirely distinct signal whose frequency element lags the original signal's frequency by 90° while maintaining the original signal's amplitude. As a result, the original signal and its Hilbert transform are orthogonal.

HT is the convolution of the signal with a $\left(\frac{1}{\pi t}\right)$ function, which highlights the local features of the signal, and it can be written as

$$H(X_1(t)) = \hat{Y}_1(t) = \left(\frac{1}{\pi t}\right) * X_1(t) \quad (25)$$

$$H(\hat{Y}_1(t)) = X_1(t) = \left(\frac{1}{\pi t}\right) * Y_1(t) \quad (26)$$

The integrals defining the convolution do not converge because X is not integrable. The Cauchy primary value is used to define HT as follows:

$$H(X_1(t)) = \frac{1}{\pi} PV \int_{-\alpha}^{\alpha} \frac{X_1(\zeta)}{t - \zeta} d\zeta = -\frac{1}{\pi} PV \int_{-\alpha}^{\alpha} \frac{X_1(t - \zeta)}{\zeta} d\zeta \quad (27)$$

A complex signal is created from HT; its imaginary component is the HT of the signal, and its fundamental component is the original signal. The analytic signal is the name provided for this signal. The momentary amplitude or envelope of the signal, which symbolizes the initial signal's low-frequency fluctuations, is the analytic signal's modulus. The following definition applies to the analytic signal with HT:

$$Z(t) = X_1(t) + j\hat{Y}_1(t) = b(t)e^{j\phi(t)} \quad (28)$$

where

$$\text{Instantaneous amplitude } b(t) = [X_1^2 + Y_1^2]^{\frac{1}{2}} \quad (29)$$

$$\text{Instantaneous phase } \phi(t) = \arctan\left(\frac{\hat{Y}_1(t)}{X_1(t)}\right) \quad (30)$$

The energy of the phase current remains unchanged over time in a healthy rotor. In contrast, damaged rotor bars cause fluctuations in the energy. The signal envelope reflects the phase current energy's fluctuation. The modules of the analytic signal formed by employing the original signal's real portion and its HT as its imaginary component are beneficial for envelope separation [36]. HT exposes signal modulation brought on by defective components. Additionally, it eliminates carrier signals, reducing irrelevant data's impact on the fault detection mechanism [37].

4.2. Fourier Transform (FT)

The FT is described mathematically using a scalar representation, and the signal is expressed as follows [38]:

$$X_s(f) = \int_{-\alpha}^{\alpha} X_s(t) e^{-2\pi i f t} dt \quad (31)$$

where $X_s(t)$ is the temporal signal.

FFT frequently gathers frequency data and converts the time domain to the frequency. The frequency data are acquired with amplitude to calculate the fault presence. Under various load levels, the magnitude and sideband frequencies vary based on the defect.

4.3. DWT

The wavelet transform, a mathematical tool, is separated into continuous and discrete techniques. The continuous wavelet transform (CWT) multiplies the signal by the wavelet coefficient and computes the transform independently for each time-domain signal [31]. The DWT is comparable to the CWT. However, the performance is faster and more comfortable. For a time-scale interpretation of the digital signal, digital filters are required. Filters with various cut-off frequencies are used to collect the various assessment scale [39]. The mother wavelet calculates the coefficients of wavelets in the initial decomposition phase. The process can be repeated if the mother wavelet is scaled and transformed. Various wavelets, including the Morlet, Harr, and Daubechies wavelets, can be used for signal decomposition. To detect broken bar failure, many signal processing methods have been developed. The DWT is the standard method for identifying rotor failure [40]. Figure 6 designates the multi-decomposition and establishes two stages of multi-resolution decomposition. In addition to processing the signal $S(n)$ with a series of high-pass filters (HPFs) to produce a high-frequency analysis (HF), the signal is handled with a series of low-pass filters (LPFs) to produce a low-frequency analysis (LF). The DWT of the signal results in the extraction of an approximation and detail signal (a and d). The decomposition process is repeated until the maximum stage of decomposition is attained [41].

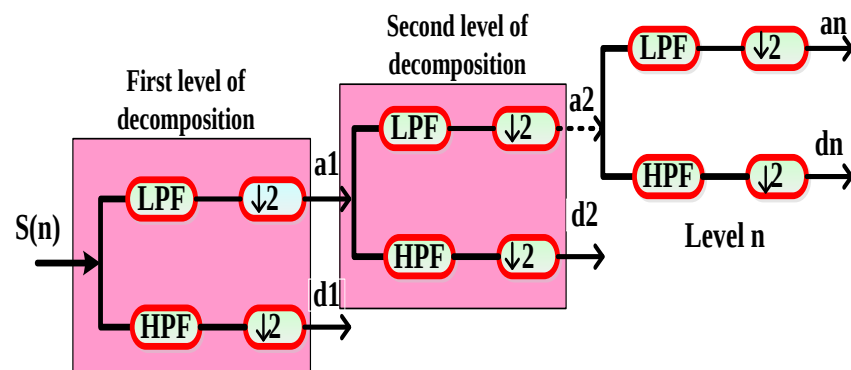


Figure 6. Multi-decomposition process.

The DWT is identical to the filter bench and was created specifically for processing sampled signals. The following equations can be used to determine the level 1 coefficients [42].

$$\begin{cases} a_1 = \sum_n^l L(n-2l) S_i(n) \\ d_1 = \sum_n^l H(n-2l) S_i(n) \end{cases} \quad (32)$$

The first signal's decomposition level has two coefficients, where a_1 is the approximate form and d_1 is the detailed version. The next decomposition level is generated using the a_1 coefficients. The level 2 coefficient can be written as follows:

$$\begin{cases} a_2 = \sum_n^l L(n-2l) a_1(n) \\ d_2 = \sum_n^l H(n-2l) a_1(n) \end{cases} \quad (33)$$

where a_2 and d_2 are the approximation and detailed signals of level 2 signals, respectively. Similar to this, all higher-level decomposition has been completed. Finally, the original signal is reconstructed, and it is represented as follows:

$$S(n) = a_n + d_n + d_{(n-1)} + \dots + d_1 \quad (34)$$

The following equation provides the number of decomposition levels n .

$$n > \frac{\log\left(\frac{f_{sa}}{f_s}\right)}{\log 2} + 1 \quad (35)$$

where f_{sa} is sampling frequency and f_s is the supply frequency.

4.4. EEV Computation

The EEV at each decomposition level is a useful diagnostic tool for assessing the severity of the fault, where the following equation is used to compute its value [43,44].

$$E_i = \sum_{k=1}^{k=n} |D_{i,k}(n)|^2 \quad (36)$$

where D is each discrete wavelet coefficients magnitude, n is the time of breakdown in DWT, and i is the level of decomposition. The EEVs of signal decomposition levels provide information that can be used for diagnosis and determining the degree of a malfunction in the IMD. The energy value deviation reflects the severity of failure for health and the defective machine.

5. Results and Discussion

An IFOC-fed IM drive's dynamic analysis in both healthy and faulty states is simulated. Appendix A illustrates the IM parameters employed in the proposed approach. To determine the impact of BRBs, the drive's performance was evaluated by varying the system's torque and fixed speed.

5.1. Simulation Results

Figure 7 illustrates the simulation results for a stable stator current, speed, and torque condition. The IM is subjected to a rotor speed of 700 rpm and torque of 10 Nm. The drive's effectiveness is tested when the torque fluctuates between 2 and 5 s while the machine operates in a healthy state. The rotor speed matches the reference speed beginning at 0.8 s during the changing torque. After 2.5 s, in a healthy condition, the electromagnetic torque matches the reference torque. The motor current and torque have reached their dynamic condition more quickly and effectively.

Table 1 illustrates the performance comparison of rotor speed with different control topologies under the dynamic variation in the reference load torque. The IFOC attains good dynamic speed control that leads to quick response under the step changes in reference torque when related to voltage/frequency (V/F), direct torque control (DTC), and input-output linearization (IOL).

Table 1. Comparison of V/F, DTC, and IFOC methods when dynamic change in reference torque from zero to maximum load.

Time Parameters	Control Methods			
	Rotor Speed			IFOC
	V/F	DTC	IOL	
		[45]		
Rise time (ts) in ms	1126	497	416	258
Maximum peak overshoot (Mp) in %	48	273	76	113
Settling time (ts) in ms	139	8	12	4

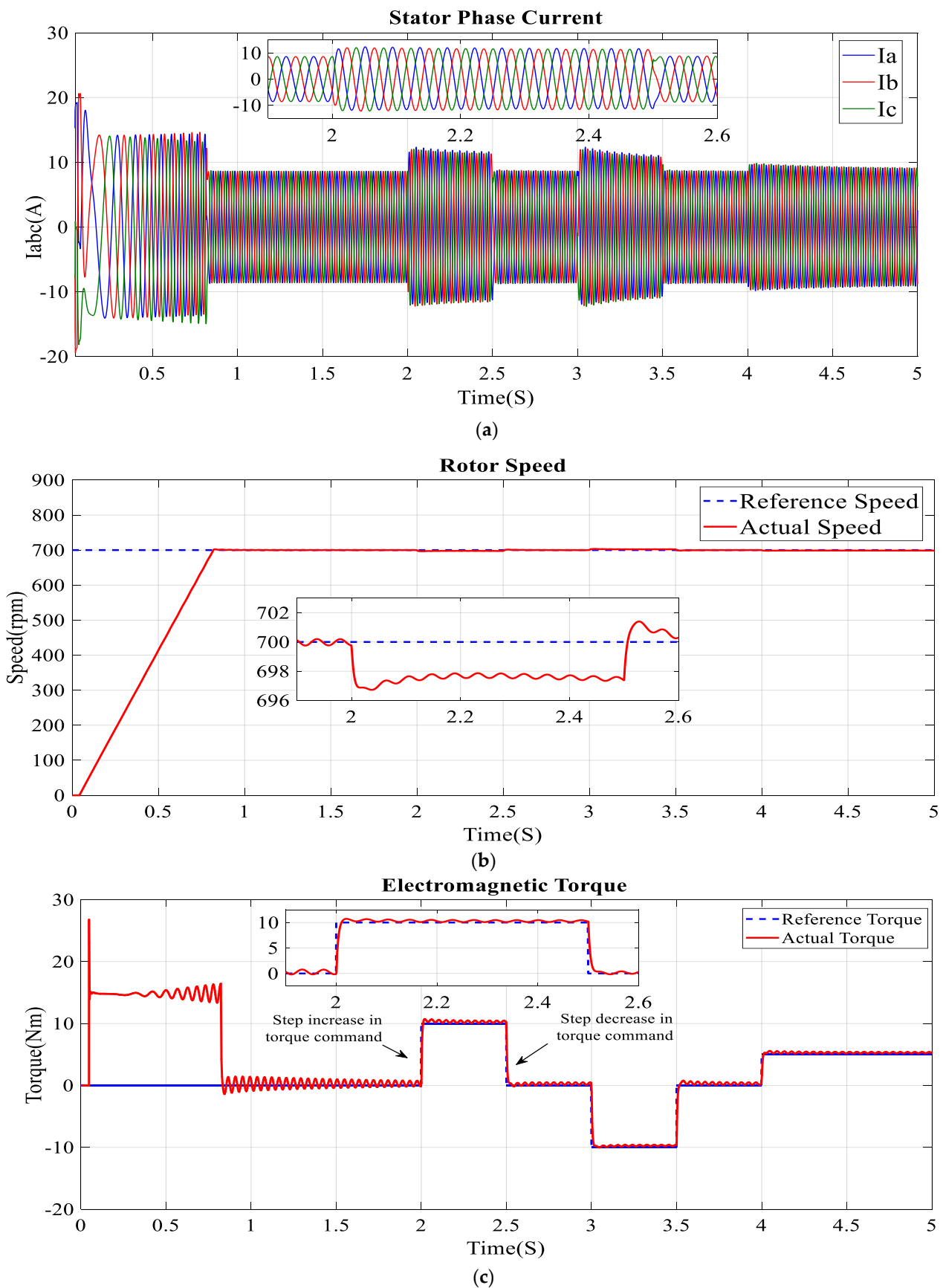


Figure 7. Healthy state of drive—(a) stator current, (b) speed, and (c) torque.

The response of a 2BRB-fault state of the motor drive is depicted in Figure 8. By raising the bar resistance specified in Equation (9), the faulty state of the induction motor is examined. The electromagnetic torque under defective conditions does not follow the dynamics for 2 to 2.5 s, and torque ripples are presented as high. During the defective state, the speed performance is impaired in 2 to 2.5 s. The speed response is reduced to 636 rpm. Additionally, compared to an IMD in a healthy condition, the magnitude of the stator currents is not maintained at the same value. The stator current amplitude is sensitive to the fault severity and the variation in load. So, there are slight oscillations at 2 to 2.5 s and 3 to 3.5 s, respectively.

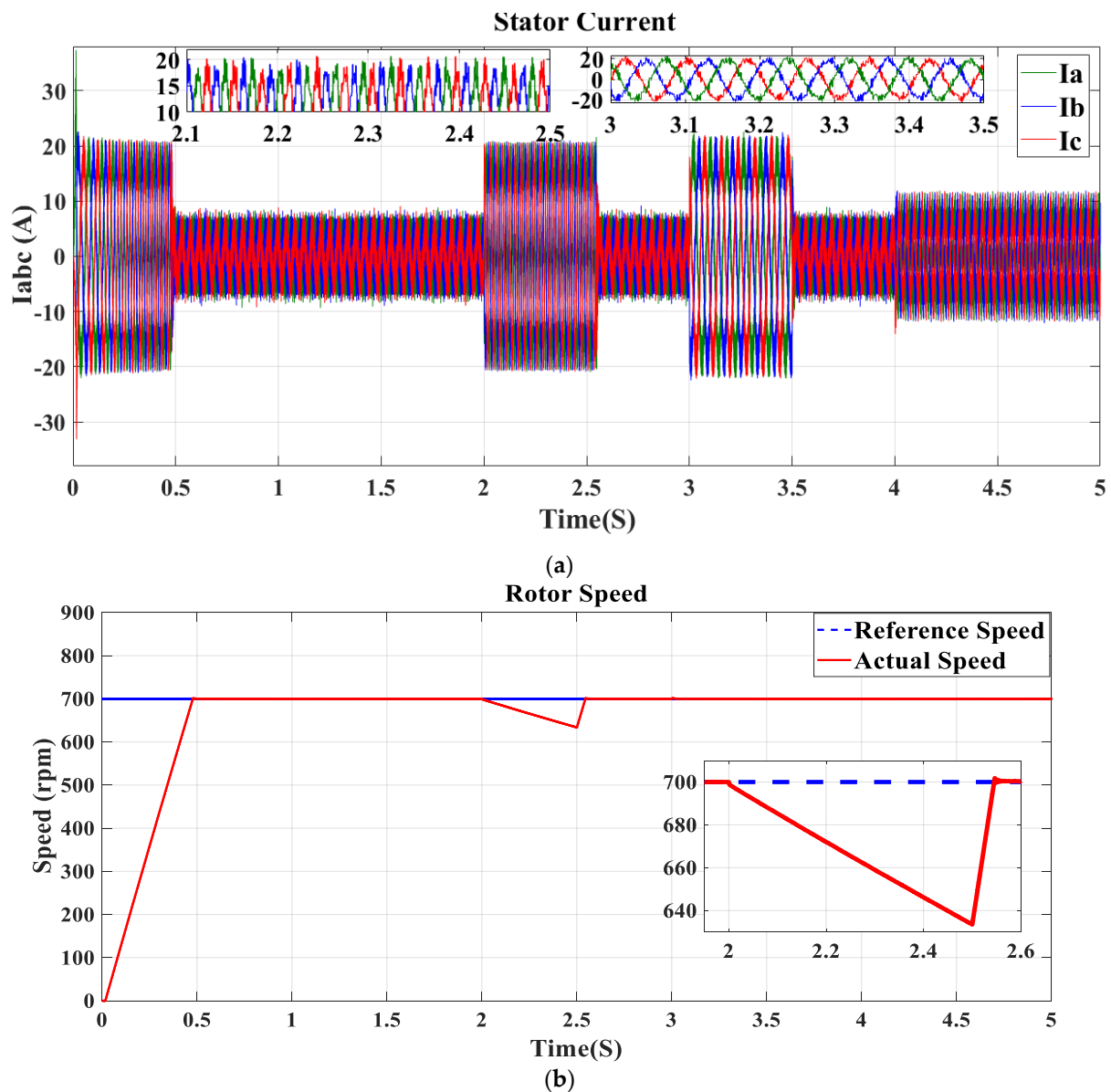


Figure 8. Cont.

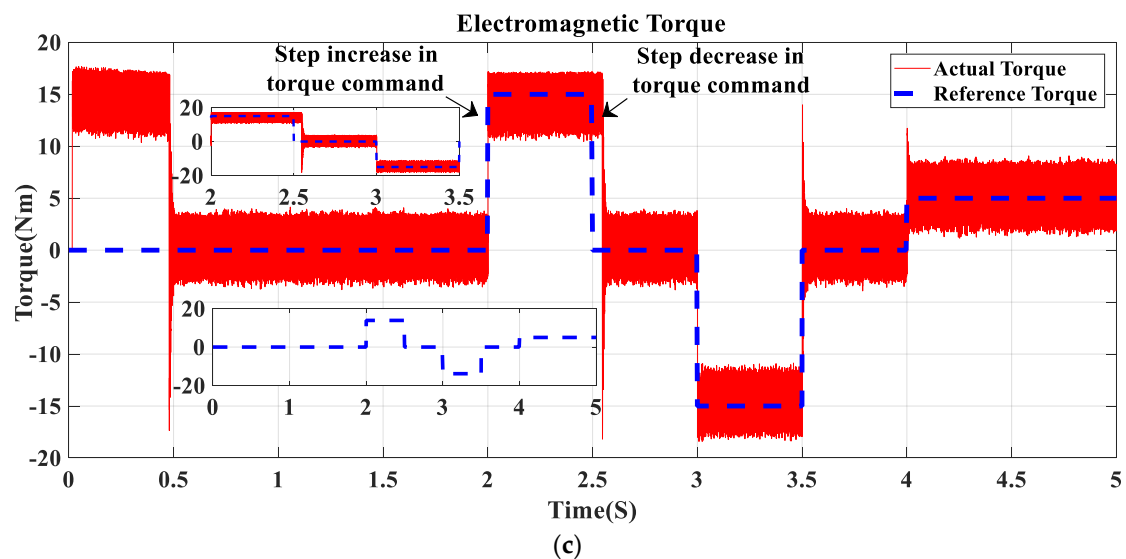


Figure 8. Faulty state of drive—(a) stator current, (b) speed, and (c) torque.

5.2. Experimental Results

Figure 9 depicts the induction machine's experimental test bench, which consisted primarily of a squirrel-cage IM, current and voltage sensors, a fault simulator, a CM system, and a TMS320F3812DSP controller. The bench had two identical induction machines—one for testing the device in a healthy condition and another for testing it in a faulty state. A fault simulator was employed to analyze the induction motor's defect characteristics. The stator current signals obtained from a machine fault simulator were employed in the investigation. Additionally, it was used to create data for both good- and bad-condition states. A 4.2 mm-diameter hole was drilled at the level point of the rotor bar to create the defect.

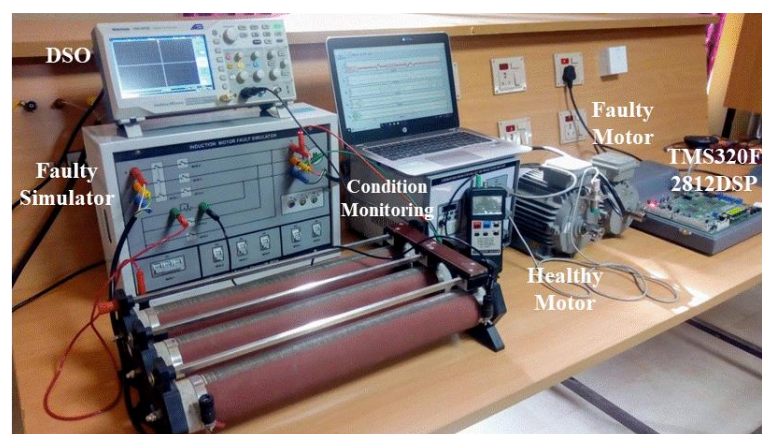


Figure 9. Experimental setup for IM drive.

Initially, the input supply voltage of 415 V was utilized to measure the functioning of the 2.2 kW IM drive in a healthy state. The DSP was then provided with the feedback data from the speed and current sensors. After the program was implemented in the DSP, the obtained real-time data was gathered and sent into MATLAB. The same procedures were used when the IM drive was in a defective state.

The various changes in speed references were carried out, and their results are displayed in Figure 10 under healthy conditions of the drive. The phase current of the stator was balanced at its rated value of 10 A, responded effectively (1 Div. = 10A), and maintained its dynamics. Without significant overshoot, the rotor's speed (1 Div. = 100 rpm) balanced

the reference value of 500 and 250 rpm. Figure 11 illustrates the experimental results of the drive in a defective state. In the defective condition, the stator current amplitude reached 13 A, which differed from the healthy state, and generated tiny oscillations during 2–2.5 s. The BRB fault caused the rotor speed's reaction to the load changes to be unstable, attaining 253 rpm. On the speed curve, the ripples represent the fault effect.

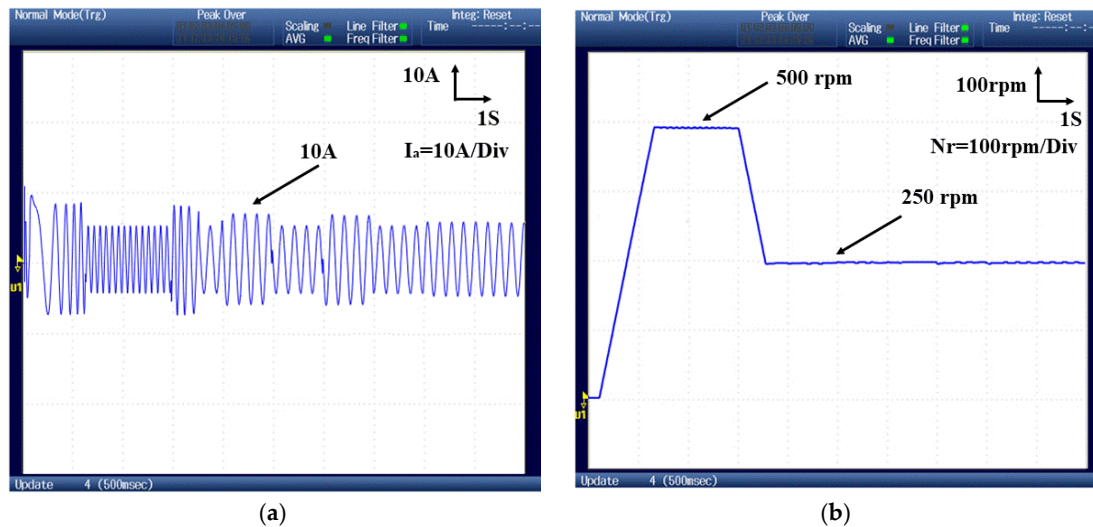


Figure 10. Experimental results of healthy state drive—(a) motor current and (b) speed.

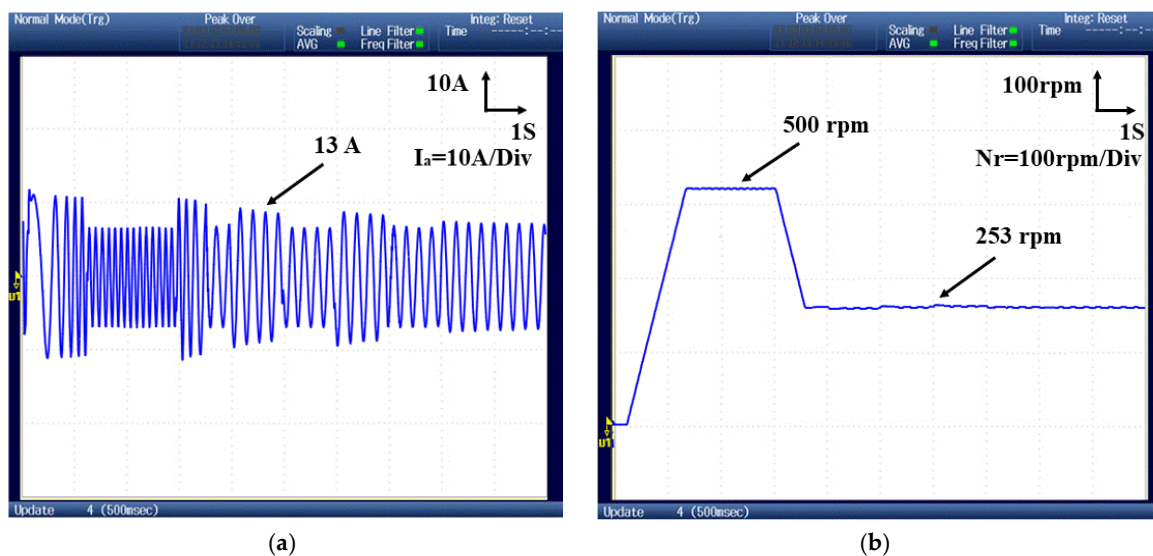


Figure 11. Experimental results of faulty state drive—(a) motor current and (b) speed.

5.3. Fault Diagnosis Using HT and DWT

The basic information was transmitted to MATLAB after extracting from the drive to find the stator current contour. The BRB faults were based on calculating the current envelope, and they could diagnose that defect using DWT.

5.3.1. HT

HT could be used to derive the envelope after observing the slip frequency and stator current. In order to determine the envelope in a closed-loop system, a set of MATLAB programs was provided. The stator current envelope is shown in both a healthy and defective state in Figure 12. The defective condition exhibited high-frequency fluctuations

between 2 to 2.5 s and 3 to 3.5 s in contrast to the healthy state. FFT could be used for frequency-data extraction based on the current envelope.

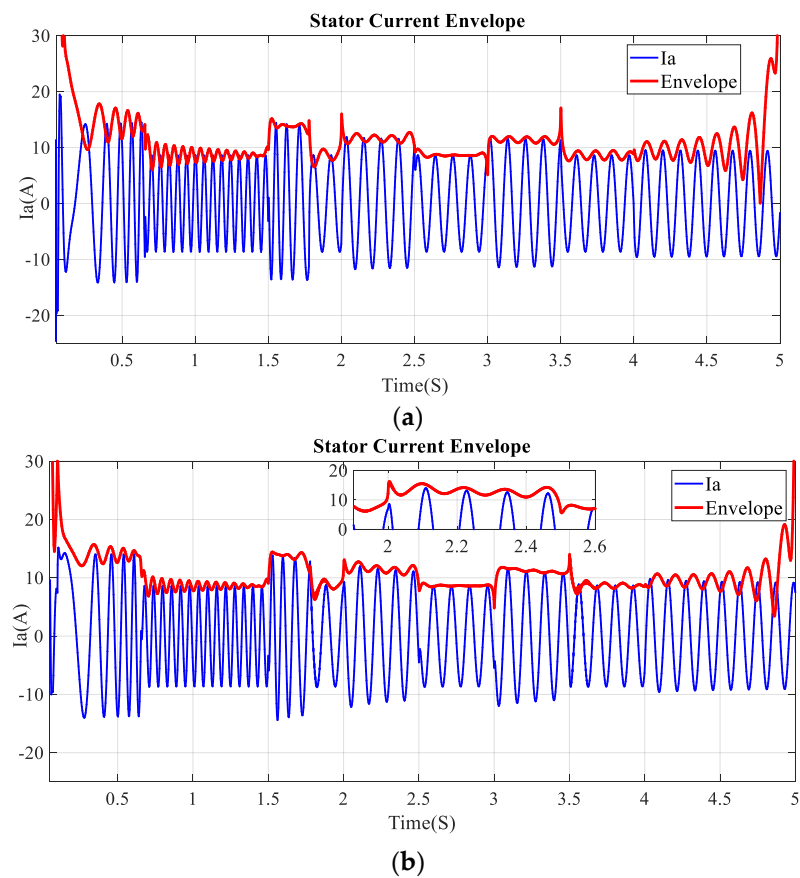


Figure 12. Envelope Identification—(a) healthy motor and (b) faulty motor.

5.3.2. FFT Analysis

The FFT analysis of the stator current for the healthy and faulty motors under transient states is shown in Figure 13. The stator current's spectral analysis used the FFT in a steady state at a nominal load. Also, the frequency parameters were extracted using FFT during the transient stage. The analysis shows the occurrence of elements directly related to the fault, which associate to the following formula: $(1 \pm 2ns)f_s$. The appearance of fault lines in the FFT spectrum demonstrates the accuracy of the fault mode.

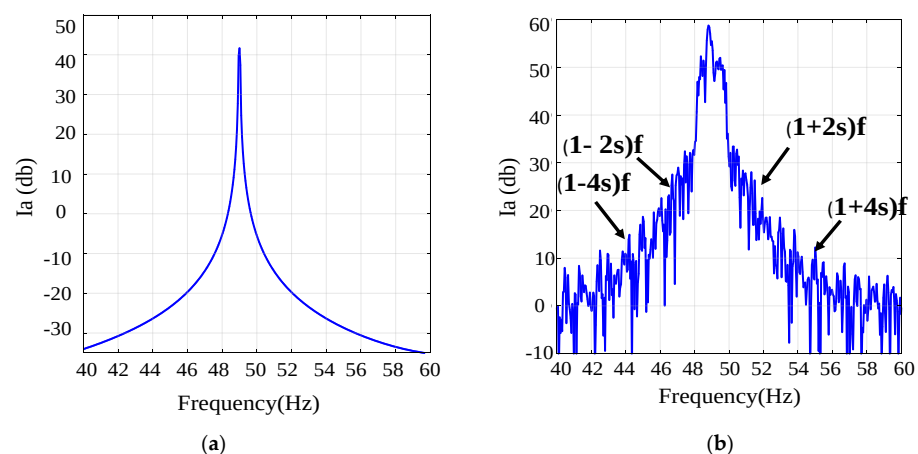


Figure 13. FFT of stator current—(a) healthy and (b) defective states.

The FFT analysis of rotor speed for the good and defective motor drives is shown in Figure 14. The speed spectra of the damaged rotor portion show the closed-loop drive's considerable deviations. The 2 sf and 4 sf harmonics of rotor speed are connected to fault harmonics. In comparison to the healthy condition, the IMD in the defective state exhibits a minor amplitude change for all sideband frequencies. There are sometimes difficulties with the FFT-based diagnosis of IM faults. So, we propose a different approach based on DWT.

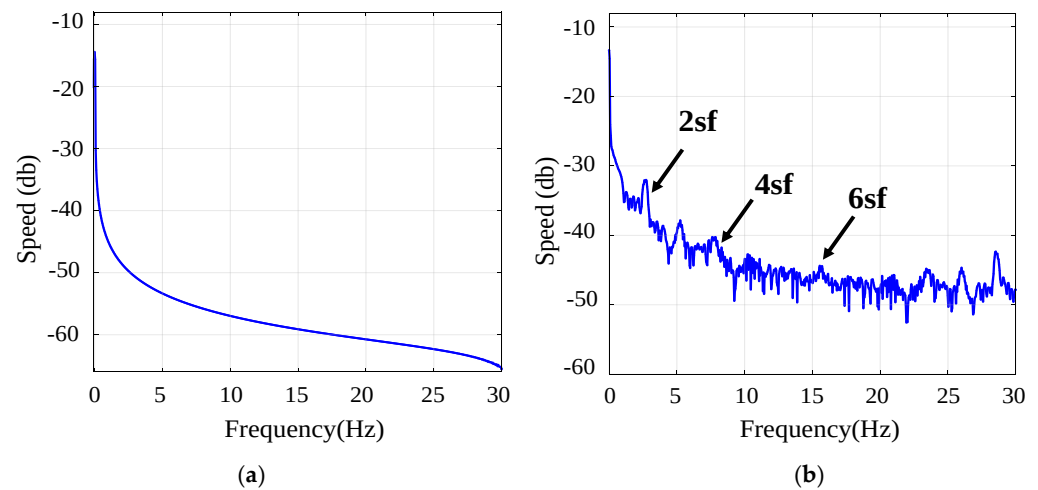


Figure 14. FFT of rotor speed—(a) healthy and (b) defective states.

5.3.3. DWT Analysis

In the DWT analysis, the mother wavelet Daubechies (db) is set to 10, and the decomposition levels are calculated using Equation (35) with a sampling frequency of 100 kHz and supply frequency of 50 Hz. There are 12 levels of decomposition, and Table 2 shows the frequency bands for each level. The stator current of each machine is decomposed using “Daubechies (db) wavelets” of varying order.

Table 2. Wavelet coefficients frequency band.

Levels	Frequency Band
d_1	25,000–50,000 Hz
d_2	12,250–25,000 Hz
d_3	6125–12,250 Hz
d_4	3062.5–6125 Hz
d_5	1531.25–3062.5 Hz
d_6	765.625–1531.25 Hz
d_7	382.81–765.625 Hz
d_8	191.40–382.81 Hz
d_9	95.70–191.40 Hz
d_{10}	47.85–95.70 Hz
d_{11}	23.926–47.85 Hz
d_{12}	11.96–23.926 Hz
a_{12}	5.98–11.96 Hz

Figures 15 and 16 demonstrate the DWT of motor current in the good and defective states, respectively. The decomposition levels for stator current signals are denoted as a_{12} , d_{12} , d_{11} , and d_{10} . When related to the healthy state, the amplitude of the a_{12} and d_{12} coefficients increase in the failure state for two BRBs because the defective condition of an IMD contains frequency components of $(1 \pm 2ns)f_s$. As a result, variations in the amplitudes of a_{12} and d_{12} develop. When the detail and approximation signals for healthy and defective machines are compared, the coefficient's magnitude a_{12} is higher in

the defective machine since they comprise the frequency elements. As a result, the DWT is a particularly effective tool for identifying damaged rotor bars in under-loaded machines.

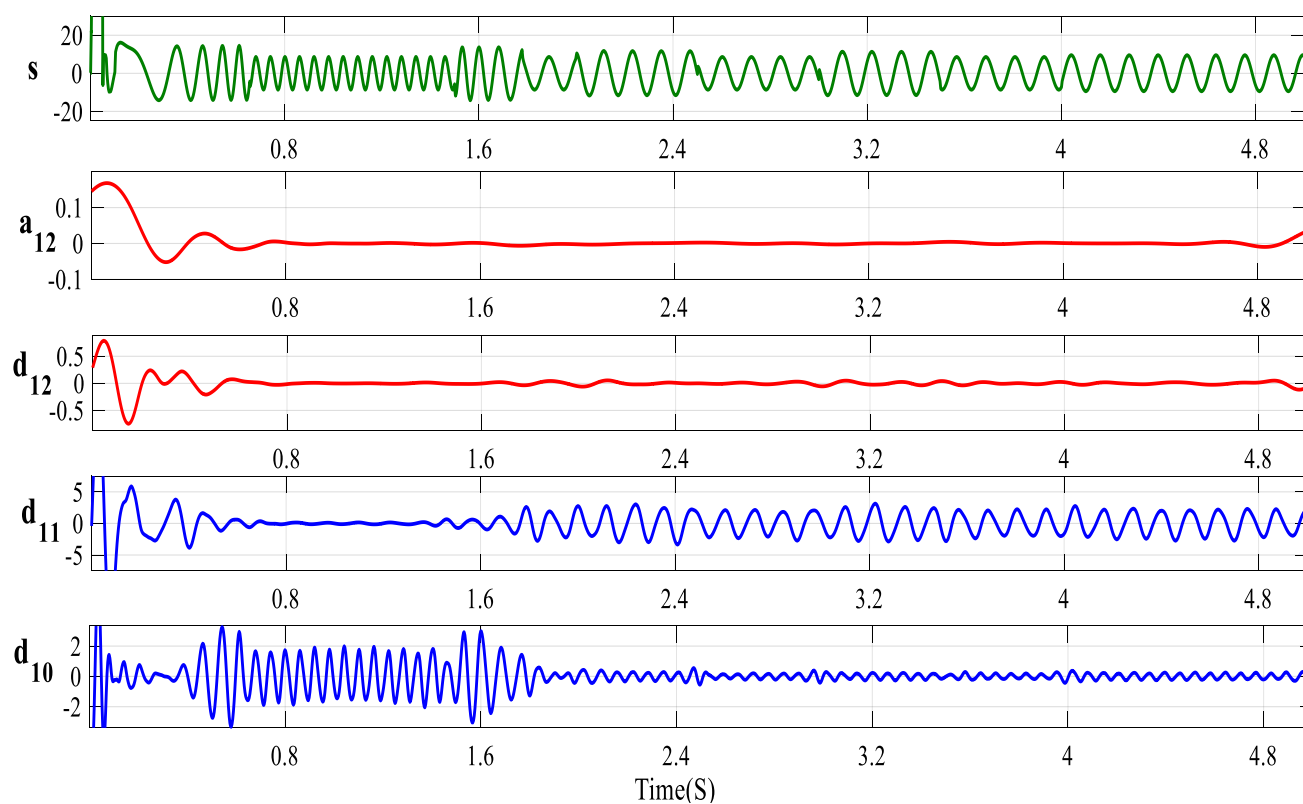


Figure 15. DWT analysis of stator current in healthy state.

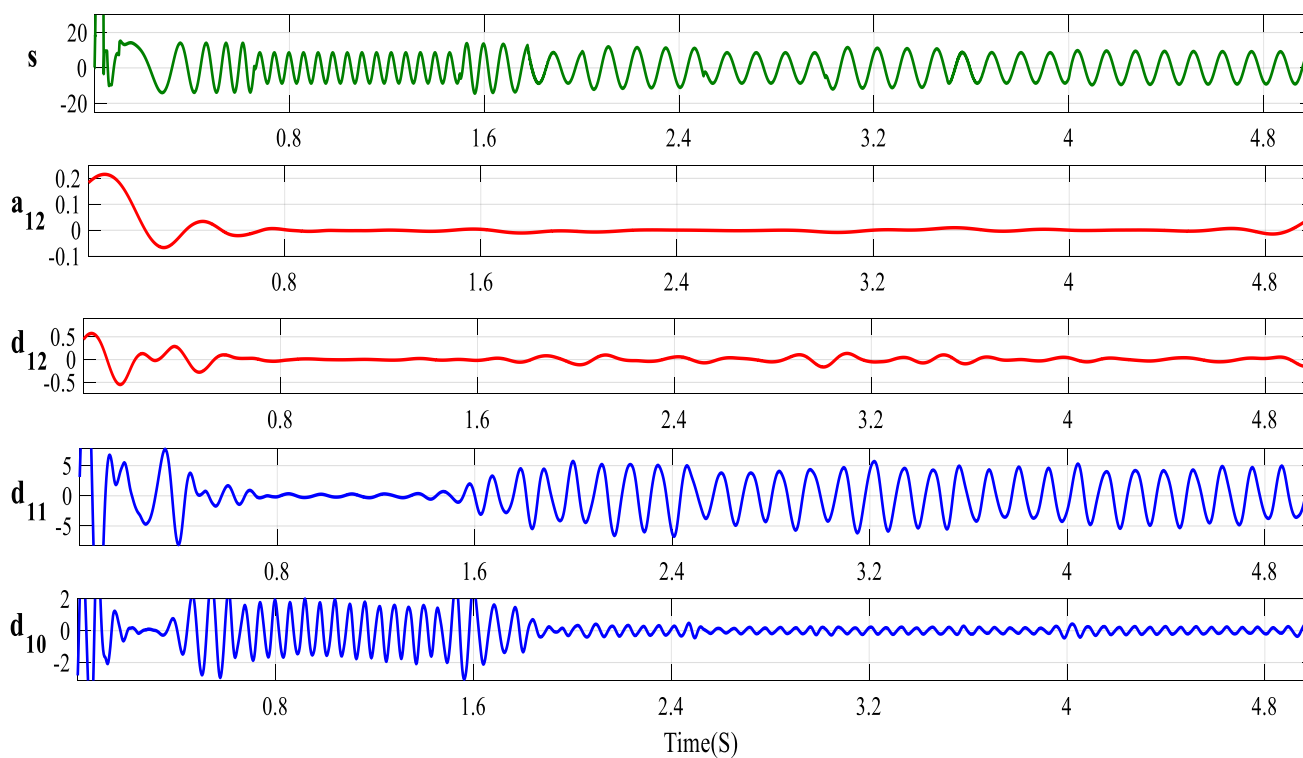


Figure 16. DWT analysis of stator current in faulty state.

Figures 17 and 18 demonstrate the DWT evaluation of rotor speed under healthy and faulty conditions, respectively. The breakdown levels for stator current signals are denoted as a_{12} , d_{12} , d_{11} , and d_{10} . According to the DWT results, there are no substantial changes in the approximations a_{12} and detailed signal d_{10} rotor speed coefficients in the healthy and defective conditions, owing to the existence of speed control loops. Small oscillations are observed in the detailed d_{12} and d_{11} coefficients, which correspond to $2sf_s$ fault harmonics. The findings of the DWT evaluation of motor current and rotor speed during both healthy and defective states can be summarized. Both results reveal an oscillation and a minor variance. The amplitude coefficient levels of faulty a_{12} , d_{12} , d_{11} , and d_{10} signals are high in both the stator current and rotor speed when compared to the healthy state of the machine.

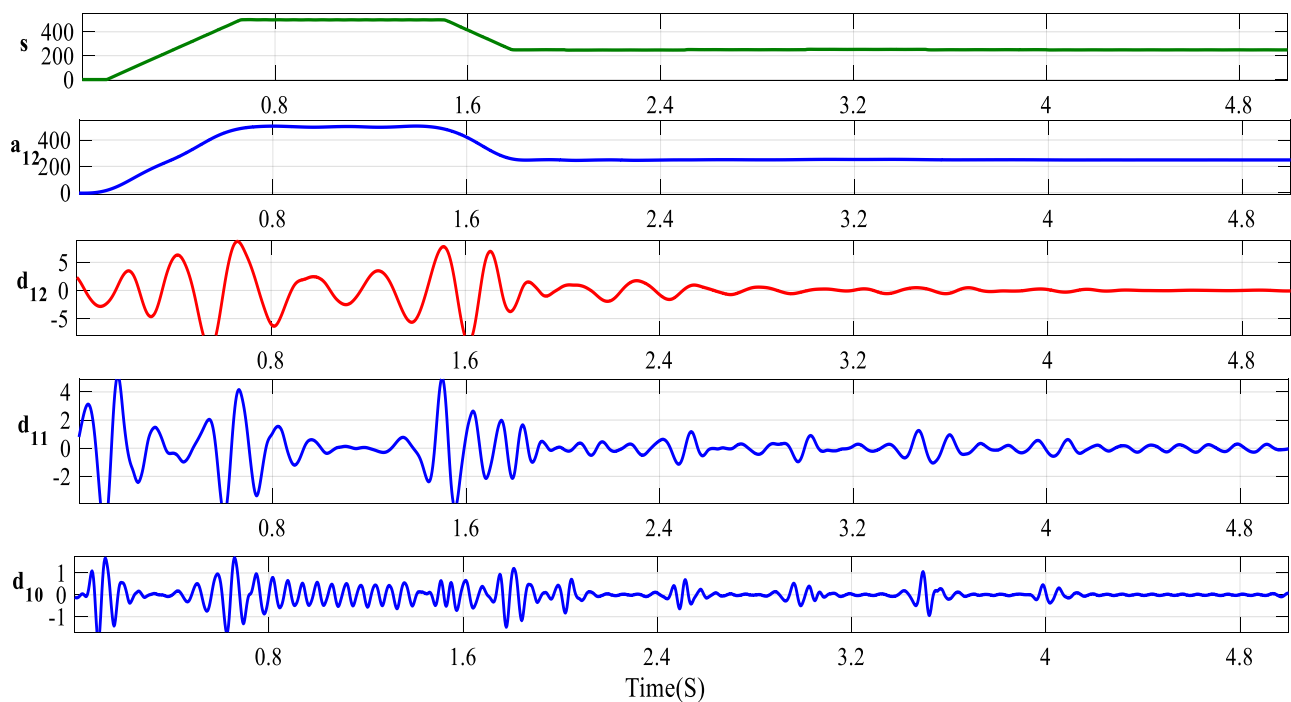


Figure 17. DWT of rotor speed in healthy state.

5.3.4. EEV Computation

The amount of energy stored at every level should be estimated in order to assess the fault severity using Equation (36) in order to show the changes brought on by the failure of the BRBs. The amount of energy held at each stator current level is seen in Figure 19. The defective state magnitude differs in a_{12} and d_{12} levels in terms of energy eigenvalue from a healthy state. For instance, 8.33% of the energy eigenvalues are increased in the faulty machine. The amount of energy held at each speed regulator setting is shown in Figure 20. The energy level in a_{12} increases by 2.17% in the BRB machine. The computation of the energy deposited for every decomposition level verifies the rise noticed in the detail and approximation signals. Levels E_{13} in the stator phase current and E_{12} in the rotor speed show the energy of this frequency band and can be utilized for identifying the severity of broken bars. This outcome will aid in fault severity analysis and serve as a reliable fault indication for closed-loop IFOC-fed IM drives.

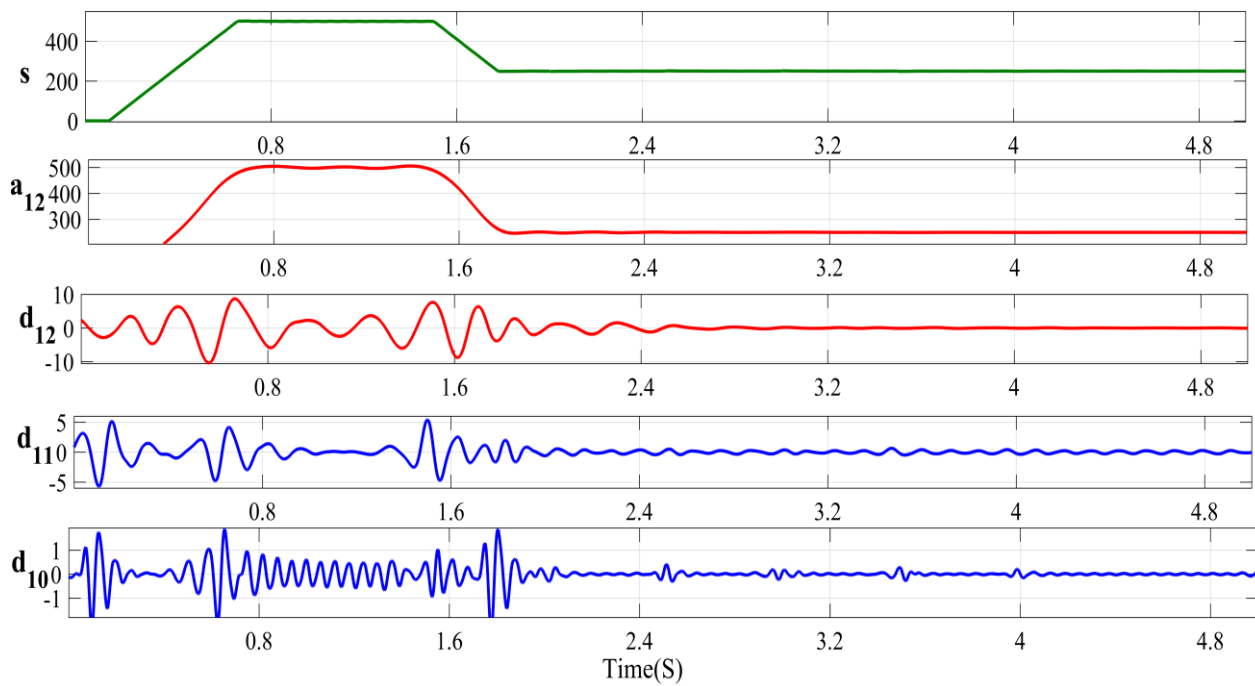


Figure 18. DWT of rotor speed in faulty state.

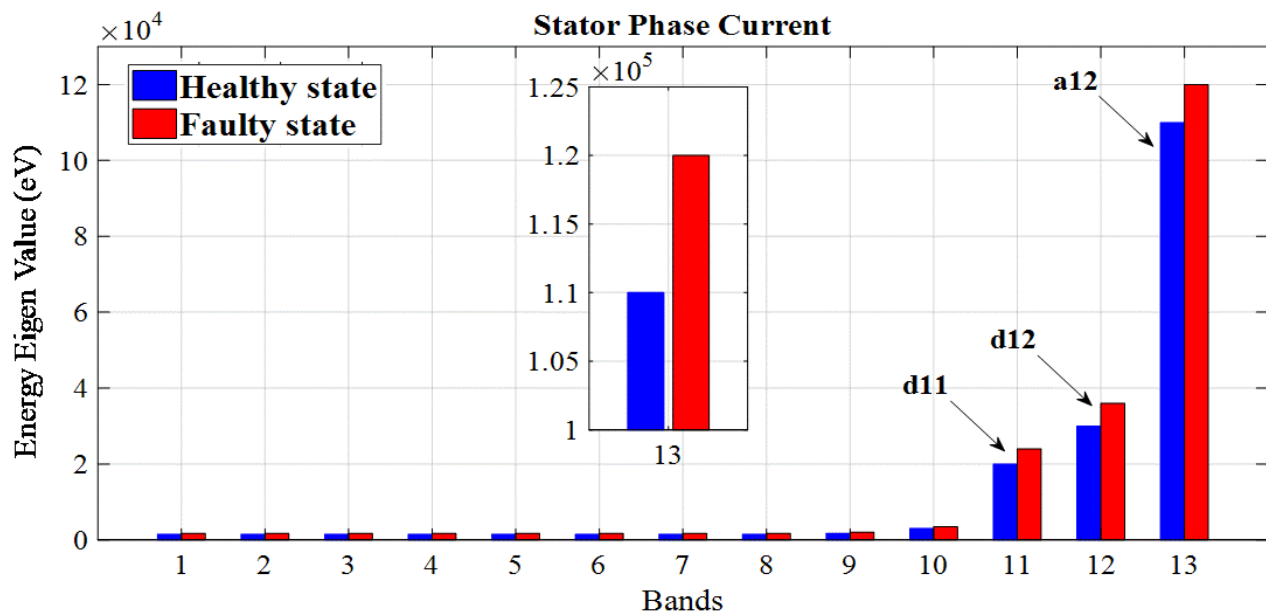


Figure 19. EEV of stator current.

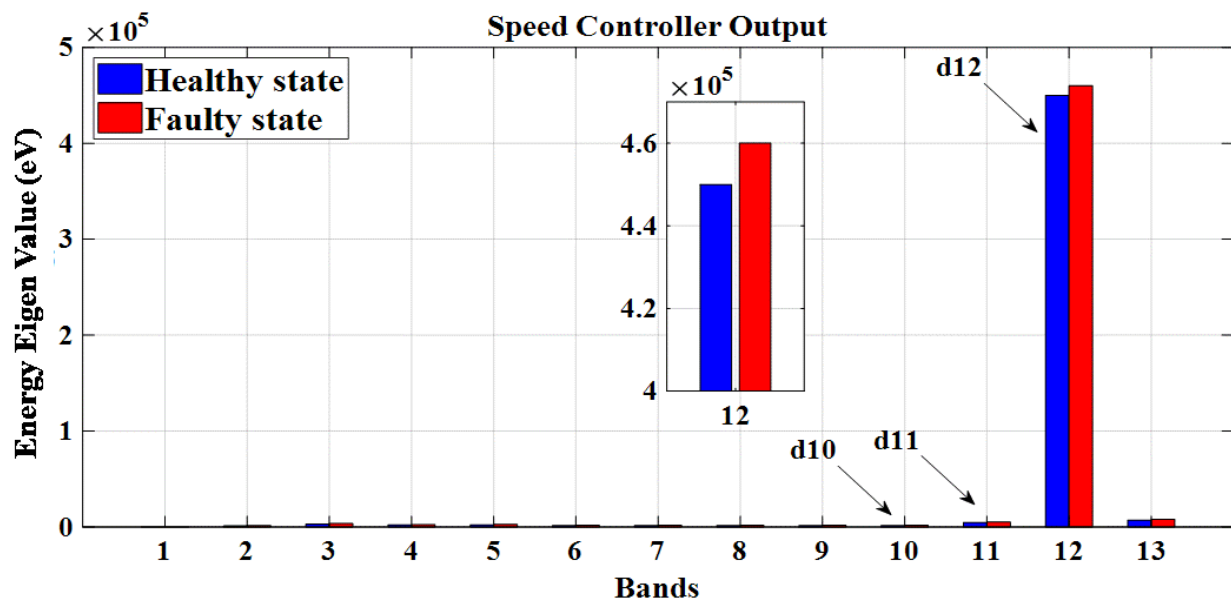


Figure 20. EEV of speed controller.

6. Discussion

The fault monitoring technique for the induction motor's closed-loop drive allows for quick problem identification and diagnosis of damaged rotor bars. To maintain the functionality of the defective IM and to look into the impact of the issue, IFOC was established. Compared to other strategies, IFOC systems offer very accurate speed tracking using their reference values and excellent time-domain features under dynamic situations, as shown in Table 1. However, defect monitoring in the IM with fluctuating loads is essential but challenging to understand, especially at low loads. In this research, the slip factor was utilized to resolve the issue of low load in particular and other loads in general. Table 3 presents a data classification based on various load situations, the number of BRBs, operation modes, controller categories, and results. The BRB fault must be found in the shortest possible time to avoid a complete shutdown. So, in this work, analysis was conducted on a machine that failed one or two BRBs. EEV calculations for both healthy and defective conditions of the machine were used to analyze the fault severity.

Table 3. Comparison of proposed methods with previous methods.

References	BRBs			Load			Mode		Validation		DOL	Control Techniques				Methods	Outcomes
	One	Two	>Two	NL	ML	FL	Steady State	Transient	Simulation	Experimental		Inverter-Fed					
												V/F	IOL	DTC	IFOC		
[1]	✓	✓				✓		✓		✓	✓					1. DWT 2. FL	FDS in OLD
[2]	✓	✓				✓	✓	✓	✓	✓					✓	1. HT 2. ANN	FDS in closed-loop IFOC drives
[4]	✓	✓		✓		✓				✓	✓					1. Wavelet packet 2. FL	FDS in OLD
[19]	✓	✓			✓		✓			✓	✓					1. HT	FDS in OLD
[21]	✓	✓			✓	✓		✓	✓	✓			✓			1. FFT 2. ANN	FD in IOL control
[25]	✓	✓			✓		✓		✓		✓					1. HT 2. ANN	Fault diagnosis in open-loop drives
[28]	✓	✓			✓			✓	✓	✓					✓	1. DWT 2. EEV	FDS in closed-loop IFOC drives
[42]			✓		✓		✓			✓				✓		1. DWT 2. EEV	FDS in DTC-fed drives
[46]		✓			✓		✓		✓	✓	✓					1. FFT 2. Current signature analysis	Fault estimation based on load torque fluctuations
[47]			✓				✓		✓	✓	✓					1. Orthogonal decomposition	Fault severity in OLD
[48]	✓	✓		✓			✓		✓	✓	✓					1. FFT 2. Torque signature analysis	FD in OLD
[49]	✓	✓		✓			✓		✓		✓					1. Multi-input convolutional neural networks	FD in OLD
[50]	✓	✓	✓	✓		✓	✓		✓		✓					1. Self-configurable ANN model	BRB fault classification in OLD
[51]	✓	✓		✓			✓			✓	✓					1. Arithmetic mean with Otsu’s method	FDS using thermal images

Table 3. Cont.

References	BRBs			Load			Mode		Validation		DOL	Control Techniques				Methods	Outcomes
	One	Two	>Two	NL	ML	FL	Steady State	Transient	Simulation	Experimental		Inverter-Fed					
												V/F	IOL	DTC	IFOC		
[52]	✓	✓	✓	✓			✓				✓				1. Rational DWT 2. Non-invasive software phase-locked loop	Multiple rotor FDS in OLD	
[53]	✓	✓		✓			✓				✓	✓			1. EEV 2. ANN	FD in OLD	
Proposed Method	✓	✓			✓	✓	✓	✓	✓	✓				✓	1. HT 2. FFT 3. DWT 4. EEV	FDS in closed-loop IFOC drives and fault severity estimation	

FD—fault detection, FDS—fault diagnosis, OLD—open-loop drives, ANN—artificial neural networks, FL—fuzzy logic.

7. Conclusions

The FD and FDS of variable speed drives are particularly complex. For this problem, a simulation and an experimental analysis of the machine in closed-loop drives utilizing an IFOC are considered. In this paper, the BRB defect in the IM is found and diagnosed using a combination of multiple signal processing tools in IFOC-fed drives. MATLAB/Simulink is used to explore the dynamic performance of the drive and fault assessment findings in closed-loop drives. The HT is used to obtain the stator current envelope to detect faults. The DWT provides useful data to diagnose the malfunctioning scenario at the variable signal. EEV determines the severity of the failure. The obtained results demonstrate the utility of HT, DWT, and EEV as defect detection tools and the simplicity of their execution in motor control applications. In the future, this work will be expanded to sensitivity analysis of rotor resistance, the identification of external electrical failures, and other mechanical issues, such as bearing and short circuit faults.

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Conflicts of Interest: There are no conflict of interest declared by the authors.

Appendix A Machines Parameters

Symbol	Parameters	Ratings
P_0	Output power	2.2 KW
V_s	Stator line voltage	415 V
L_s	Stator resistance	6.81 Ω
R_r	Rotor resistance	5.24 Ω
R_b	Rotor bar resistance	0.21 m Ω
M_{st}	Mutual inductance	63.24 mH
L_b	Rotor bar inductance	0.13 mH
L_{sf}	Stator leakage inductance	22.5 mH
T_L	Load torque	10 Nm
n_b	Rotor bars	16

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