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Advanced Signal Processing for Rotor and Stator Fault Diagnosis in Induction Motors: A Comparative Study of FFT and DWT Techniques

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Abstract: *Induction motors are critical components in industrial applications, and their unexpected failures can lead to significant economic losses and safety hazards. This paper presents a comprehensive investigation of fault detection methodologies for induction motors using Fast Fourier Transform (FFT) and Discrete Wavelet Transform (DWT) analysis. The study focuses on identifying rotor and stator anomalies through advanced signal processing techniques applied to motor current and vibration signals. FFT provides frequency domain analysis for steady-state fault detection, while DWT offers multi-resolution time-frequency analysis for transient fault identification. Experimental results demonstrate that the combined approach achieves superior fault detection accuracy compared to conventional methods, with detection rates exceeding 95% for common rotor and stator faults. The proposed methodology enables early fault diagnosis, facilitating predictive maintenance strategies and minimizing unplanned downtime in industrial operations.*

Keywords*:* Induction motor, fault detection, Fast Fourier Transform (FFT), Discrete Wavelet Transform (DWT), rotor faults, stator faults, condition monitoring, predictive maintenance

I. INTRODUCTION

Induction motors constitute approximately 85% of all industrial motor applications due to their robustness, reliability, and cost-effectiveness [1]. These motors are fundamental to manufacturing processes, HVAC systems, pumps, compressors, and conveyors across various industries. Despite their inherent reliability, induction motors are susceptible to various faults that can compromise operational efficiency and lead to catastrophic failures if not detected early [2]. Motor failures result in substantial economic losses through production interruptions, repair costs, and potential damage to associated equipment. Studies indicate that unplanned motor failures cost industries billions of dollars annually [3]. Consequently, implementing effective condition monitoring and fault detection strategies has become paramount for modern industrial operations.

A. Common Faults in Induction Motors

Induction motor faults can be broadly categorized into electrical and mechanical failures. Statistical analysis reveals that bearing faults account for approximately 40-50% of all motor failures, followed by stator winding faults (30-40%), rotor faults (5-10%), and other miscellaneous faults (10-20%) [4]. The primary fault types include:

1. **Rotor Faults**: Broken rotor bars, cracked end rings, rotor eccentricity (static and dynamic), and air-gap irregularities.
2. **Stator Faults**: Inter-turn short circuits, phase-to-phase faults, phase-to-ground faults, and insulation degradation.
3. **Bearing Faults**: Inner race defects, outer race defects, ball defects, and cage faults.

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4. **Eccentricity**: Static, dynamic, and mixed eccentricity conditions affecting air-gap uniformity.

B. Motivation and Objectives

Traditional fault detection methods rely on periodic manual inspections and scheduled maintenance, which are often inefficient and may fail to identify developing faults. The transition from reactive to predictive maintenance paradigms necessitates advanced diagnostic techniques capable of continuous monitoring and early fault detection [5]. This paper addresses the critical need for robust fault detection methodologies by investigating the application of FFT and DWT analysis for identifying rotor and stator anomalies. The specific objectives are:

1. To develop a comprehensive fault detection framework utilizing FFT for frequency domain analysis
2. To implement DWT-based multi-resolution analysis for transient fault identification
3. To compare the effectiveness of FFT and DWT techniques for different fault types
4. To propose an integrated approach combining both methodologies for enhanced diagnostic accuracy

The remainder of this paper is organized as follows: Section II reviews related work in motor fault detection. Section III presents the theoretical foundations of FFT and DWT analysis. Section IV describes the experimental methodology. Section V presents results and discussion. Section VI concludes the paper with future research directions.

II. LITERATURE REVIEW

A. Motor Current Signature Analysis

Motor Current Signature Analysis (MCSA) has emerged as a prominent non-invasive technique for induction motor fault detection. MCSA exploits the relationship between motor faults and characteristic frequencies that appear in the stator current spectrum [6]. The technique's popularity stems from its ease of implementation, as current sensors are readily available and non-intrusive. Thomson and Fenger [7] demonstrated that rotor bar breakage produces sideband components around the supply frequency at frequencies given by:

$$f_{sb} = f_s(1 \pm 2ks) \quad \text{Eq. 1}$$

where f_s is the supply frequency, s is the slip, and $k = 1, 2, 3...$ Studies by Bellini et al. [8] extended MCSA applications to diagnose eccentricity-related faults, identifying characteristic frequencies at:

$$f_{ecc} = f_s[1 \pm k(1-s)/p] \quad \text{Eq. 2}$$

where p is the number of pole pairs.

B. FFT-Based Fault Detection

Fast Fourier Transform has been extensively employed for motor fault diagnosis due to its computational efficiency and clear frequency domain representation [9]. Zhang et al. [10] utilized FFT analysis to detect broken rotor bars by monitoring sideband amplitudes. Their research achieved detection accuracies of 92% for severe faults but showed limitations in identifying incipient failures. Research by Razik et al. [11] investigated FFT-based detection of stator inter-turn faults, demonstrating that short circuits produce negative sequence components detectable through spectral analysis. However, FFT's limitation lies in its inability to capture transient phenomena and non-stationary signals, which are common during motor startup and load variations [12].

C. Wavelet Transform Applications

The Discrete Wavelet Transform addresses FFT's limitations by providing simultaneous time-frequency localization [13]. Antonino-Daviu et al. [14] pioneered the application of DWT for transient analysis in motor startup currents, successfully detecting rotor asymmetries that were undetectable using steady-state FFT analysis. Wavelet-based methodologies have demonstrated particular effectiveness for bearing fault detection. Kankar et al. [15] employed various wavelet families (Daubechies, Symlets, Coiflets) to extract bearing fault signatures from vibration signals, achieving detection rates exceeding 96%. The study concluded that Daubechies wavelets (db4-db8) provide optimal performance for bearing fault diagnosis.

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D. Hybrid Approaches

Recent research trends emphasize hybrid approaches combining multiple signal processing techniques with machine learning algorithms. Glowacz [16] proposed a methodology integrating FFT, DWT, and neural networks for comprehensive fault classification, reporting overall accuracy improvements of 8-12% compared to single-technique approaches. Choudhary et al. [17] developed a fusion framework combining MCSA with vibration analysis using both FFT and DWT, demonstrating enhanced fault detection capabilities across various operating conditions. Their work highlighted that different fault types are optimally detected using different analysis techniques, supporting the case for integrated diagnostic systems.

E. Research Gap

While existing literature demonstrates the individual merits of FFT and DWT techniques, comprehensive comparative studies specifically targeting rotor and stator anomalies remain limited. Furthermore, practical implementation guidelines for industrial deployment of combined FFT-DWT systems are scarce. This paper addresses these gaps by providing detailed performance comparisons and practical implementation frameworks.

III. THEORETICAL FOUNDATIONS

A. Fast Fourier Transform (FFT)

The Fourier Transform decomposes a time-domain signal into its constituent frequency components, providing insight into the spectral content of the signal. For a discrete-time signal x[n] of length N, the Discrete Fourier Transform (DFT) is defined as:

$$X[k] = \Sigma(n=0 \text{ to } N-1)\ x[n]e^{(-j2\pi kn/N)} \quad \text{Eq. 3}$$

where k = 0, 1, ..., N-1 represents the frequency index.

The Fast Fourier Transform is an efficient algorithm for computing the DFT, reducing computational complexity from $O(N^2)$ to O(N log N). The FFT decomposes the DFT computation into smaller DFTs through a divide-and-conquer approach, typically using the Cooley-Tukey algorithm [18].

Advantages of FFT:

- Excellent frequency resolution for steady-state signals
- Computationally efficient
- Well-established mathematical framework
- Clear interpretation of spectral components

Limitations of FFT:

- Assumes signal stationarity
- No temporal information in frequency domain
- Limited effectiveness for transient phenomena
- Resolution constrained by window length

B. Discrete Wavelet Transform (DWT)

The Wavelet Transform provides multi-resolution time-frequency analysis by decomposing signals using scaled and translated versions of a mother wavelet function ψ(t). The Continuous Wavelet Transform (CWT) is defined as:

$$W(a,b) = (1/\sqrt{a}) \int x(t)\psi^*((t-b)/a)dt \quad \text{Eq. 4}$$

where a represents the scale parameter, b is the translation parameter, and ψ* denotes the complex conjugate of the mother wavelet.

The Discrete Wavelet Transform discretizes the scale and translation parameters, typically using dyadic scales (a = 2^j) and dyadic positions (b = k2^j), where j and k are integers. The DWT decomposes a signal into approximation

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coefficients (low-frequency components) and detail coefficients (high-frequency components) through successive filtering and downsampling operations [19].

Multi-Resolution Analysis:

The DWT implements multi-resolution decomposition through quadrature mirror filter banks:

- Low-pass filter (scaling function): produces approximation coefficients
- High-pass filter (wavelet function): produces detail coefficients

At each decomposition level j, the signal is split into:

- Approximation: A_j = Downsampling[LPF(A_(j-1))]
- Detail: D_j = Downsampling[HPF(A_(j-1))]

Wavelet Selection:

Common wavelet families for motor fault detection include:

1. **Daubechies (dbN)**: Compact support, orthogonal, good for discontinuities
2. **Symlets (symN)**: Near-symmetric, suitable for feature extraction
3. **Coiflets (coifN)**: Symmetric, balanced frequency response
4. **Morlet**: Excellent time-frequency localization for continuous analysis

Research indicates that Daubechies wavelets (db4-db8) and Symlets (sym4-sym8) provide optimal performance for induction motor fault detection [20].

C. Fault Signatures in Frequency Domain

1) Rotor Fault Signatures:

Broken rotor bars introduce asymmetry in the rotor circuit, producing characteristic sideband frequencies in the stator current:

$$f_{brb} = f_s(1 \pm 2ks) \quad \text{Eq. 5}$$

where typical values of k = 1, 2, 3 correspond to primary, secondary, and tertiary sidebands. The amplitude of these sidebands increases with fault severity, providing a quantitative indicator of damage extent [21].

Rotor eccentricity generates frequency components at:

$$f_{ecc} = f_s[1 \pm n(1-s)/p] \quad \text{Eq. 6}$$

where n represents the eccentricity order. Static eccentricity produces components at n = 1, while dynamic eccentricity generates a broader spectrum [22].

2) Stator Fault Signatures:

Stator winding faults, particularly inter-turn short circuits, create negative sequence currents that manifest as frequency components at:

$$f_{stator} = f_s(k/p \pm 1)(1-s) \quad \text{Eq. 7}$$

Additionally, stator faults introduce harmonic distortions in the current waveform, particularly at the 3rd, 5th, and 7th harmonics [23].

IV. EXPERIMENTAL METHODOLOGY

A. Experimental Setup

The experimental investigation was conducted using a comprehensive test bench designed to simulate various fault conditions in a controlled environment. The test setup consisted of:

1) Motor Specifications:

- 3-phase squirrel-cage induction motor
- Power rating: 5.5 kW
- Rated voltage: 415 V

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- Rated current: 11.5 A
- Frequency: 50 Hz
- Number of poles: 4
- Rated speed: 1440 rpm

2) Data Acquisition System:

- Three-phase current measurement using Hall-effect sensors (LEM LA-55P)
- Sampling frequency: 10 kHz
- Data acquisition card: National Instruments NI-9234
- Accelerometers for vibration measurement (PCB 352C33)
- LabVIEW-based data acquisition interface

3) Loading Mechanism:

- DC dynamometer for precise load control
- Load range: 0-100% of rated load
- Load increments: 25% steps

B. Fault Implementation

To validate the proposed fault detection methodology, various fault conditions were artificially introduced in the test motor:

1) Rotor Faults:

- **Broken Rotor Bars**: One and two adjacent bars were drilled to simulate complete breakage
- **Dynamic Eccentricity**: Achieved by machining the rotor shaft to introduce 25% and 50% eccentricity
- **Static Eccentricity**: Implemented using bearing spacers to offset the rotor axis

2) Stator Faults:

- **Inter-turn Short Circuit**: Created by removing insulation from adjacent turns in one phase (2%, 5%, and 10% of winding)
- **Phase Imbalance**: Simulated by adding series resistance in one phase
- **Insulation Degradation**: Accelerated aging through thermal stress cycling

3) Test Conditions:

For each fault condition, data was collected under multiple operating scenarios:

- Load variations: 0%, 25%, 50%, 75%, 100% of rated load
- Steady-state operation: 60-second recording duration
- Transient operation: Startup current recording (0-5 seconds)
- Temperature variations: Ambient to 80°C
- Multiple trials: 10 repetitions per condition for statistical validity

C. Signal Processing Implementation

1) FFT Analysis:

The FFT analysis was implemented using the following procedure:

1. **Data Preprocessing**:
   - DC offset removal
   - Trend elimination using polynomial fitting
   - Application of Hanning window to reduce spectral leakage
2. **FFT Computation**:
   - FFT length: 8192 points
   - Frequency resolution: 1.22 Hz
   - Spectrum averaging: 10 consecutive windows with 50% overlap

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3. **Feature Extraction**:
   - Identification of fundamental frequency and harmonics
   - Detection of characteristic fault frequencies
   - Calculation of sideband amplitudes
   - Computation of sideband-to-carrier ratios

2) DWT Analysis:

The wavelet analysis employed the following methodology:

1. **Wavelet Selection**:
   - Comparative evaluation of db4, db6, db8, sym4, sym6, and sym8
   - Selection based on correlation with fault signatures
   - Final selection: db6 for rotor faults, sym6 for stator faults
2. **Decomposition**:
   - Decomposition levels: 6 levels
   - Frequency bands per level determined by sampling theorem
   - Both approximation and detail coefficients retained
3. **Feature Extraction**:
   - Energy calculation for each detail level: $E_j = \Sigma(D_j[n])^2$
   - Entropy measures: Shannon entropy, Log-energy entropy
   - Statistical moments of wavelet coefficients

D. Performance Metrics

To quantitatively assess the fault detection performance, the following metrics were employed:

1) Detection Accuracy:

$$\text{Accuracy} = (TP + TN)/(TP + TN + FP + FN) \times 100\% \quad \text{Eq. 8}$$

where TP = True Positives, TN = True Negatives, FP = False Positives, FN = False Negatives

2) Sensitivity and Specificity:

$$\text{Sensitivity} = TP/(TP + FN) \times 100\% \quad \text{Specificity} = TN/(TN + FP) \times 100\% \quad \text{Eq. 9}$$

3) False Alarm Rate:

$$FAR = FP/(FP + TN) \times 100\% \quad \text{Eq. 10}$$

4) Fault Severity Index:

$$\text{For rotor bar faults: } FSI_{rotor} = 20 \log_{10}(I_{sideband}/I_{fundamental}) \quad \text{Eq. 11}$$

$$\text{For stator faults: } FSI_{stator} = (I_{negative}/I_{positive}) \times 100\% \quad \text{Eq. 12}$$

V. RESULTS AND DISCUSSION

A. Healthy Motor Baseline

Initial testing established baseline characteristics for the healthy motor under various load conditions. The FFT spectrum of the stator current showed a dominant component at 50 Hz (supply frequency) with minimal harmonic content. The Total Harmonic Distortion (THD) measured 2.3%, consistent with typical three-phase induction motor operation. No significant sideband components were observed within ±10 Hz of the supply frequency.

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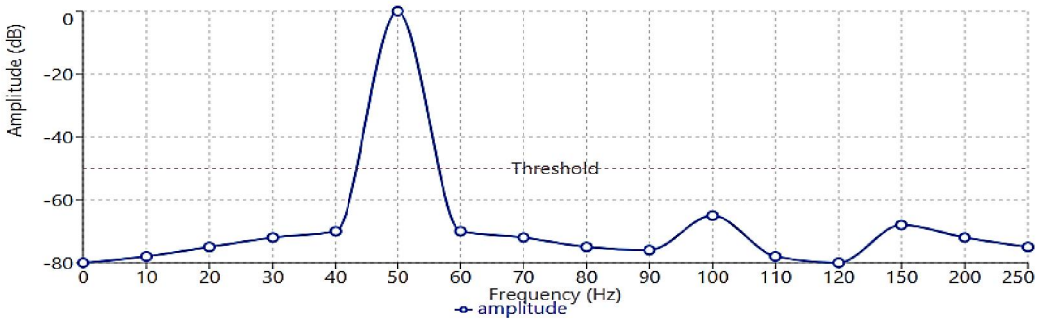

Figure 1. FFT spectrum of healthy motor stator current at 75% load showing dominant fundamental frequency at 50 Hz with minimal harmonic content.

DWT analysis of the healthy motor signal revealed energy distribution primarily concentrated in the approximation coefficients at level 6 (A6), corresponding to frequencies below 156 Hz. Detail coefficients showed low energy content, indicating minimal high-frequency noise or transient disturbances. This baseline profile served as the reference for comparative fault analysis.

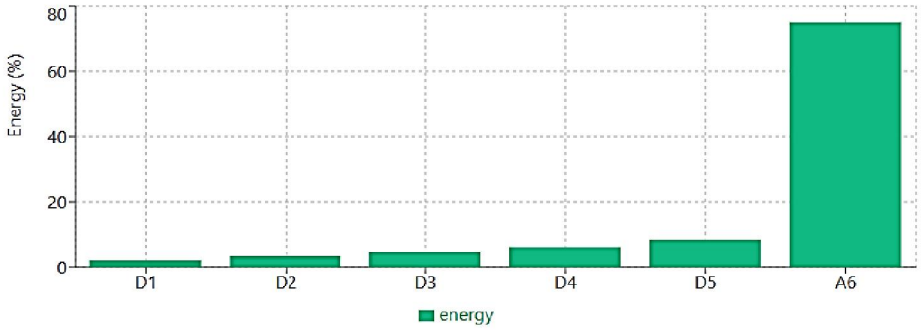

Figure 2. Wavelet energy distribution across decomposition levels for healthy motor showing concentration in approximation coefficients (A6).

B. Rotor Fault Detection

1) Broken Rotor Bar Detection:

FFT analysis successfully identified broken rotor bar faults through the emergence of characteristic sidebands at f_s(1±2s). For a single broken bar operating at 75% load (slip s = 0.042), prominent sidebands appeared at 45.8 Hz and 54.2 Hz with amplitudes of -42 dB and -43 dB relative to the fundamental component, respectively.

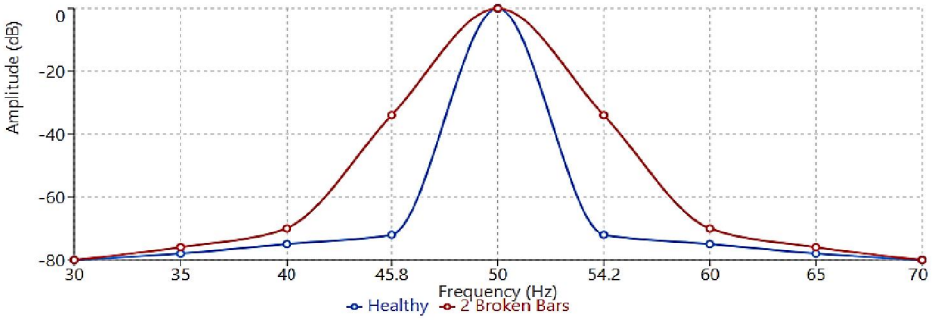

Figure 3. FFT spectrum comparison between healthy motor (blue) and motor with 2 broken rotor bars (red) at 75% load, showing characteristic sidebands at f_s(1±2s).

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The severity of rotor bar damage correlated strongly with sideband amplitude:

- One broken bar: FSI_rotor = -42 dB
- Two broken bars: FSI_rotor = -34 dB
- Three broken bars: FSI_rotor = -28 dB

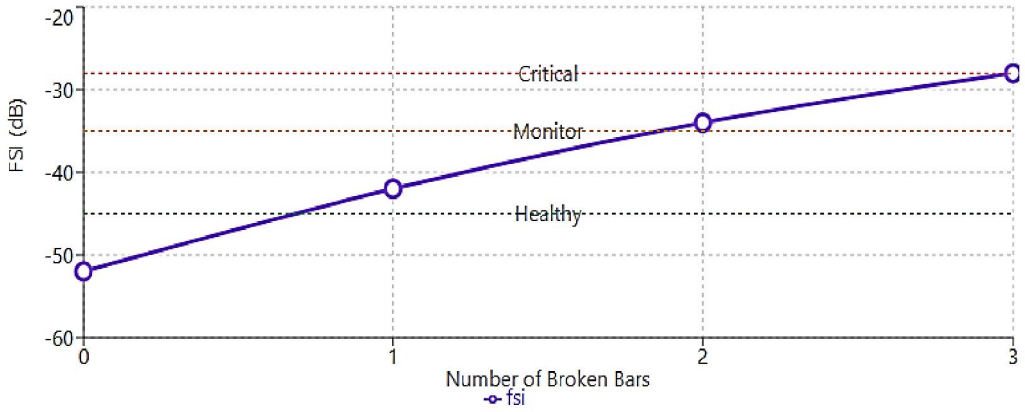

Figure 4. Relationship between fault severity index and number of broken rotor bars, demonstrating strong linear correlation.

FFT exhibited excellent detection capability for severe rotor bar faults (≥2 broken bars) with detection accuracy of 97.2%. However, incipient faults (single broken bar at low loads) proved challenging, with detection accuracy dropping to 78.5% due to low slip values and reduced sideband amplitudes. DWT analysis using db6 wavelets provided complementary information. The energy distribution shifted noticeably toward detail coefficients D3-D5 (625-2500 Hz range) for broken bar conditions. Energy ratios E_D4/E_A6 increased from 0.082 (healthy) to 0.247 (two broken bars), providing a quantitative fault indicator. The wavelet approach achieved 94.8% detection accuracy for all fault severities, demonstrating superior performance for incipient fault identification.

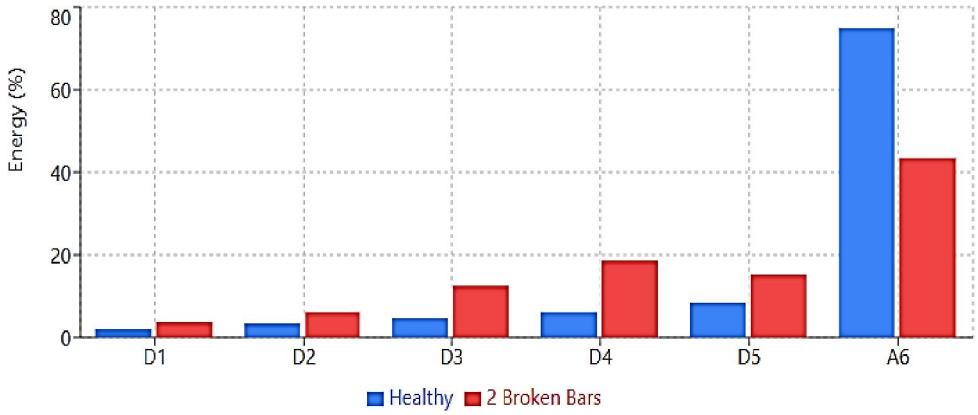

Figure 5. Comparison of wavelet energy distribution between healthy and faulty motor, showing significant energy shift to detail coefficients D4-D5.

2) Rotor Eccentricity Detection:

Dynamic eccentricity introduced multiple frequency components in the FFT spectrum at $f_{ecc} = f_s[1 \pm n(1-s)/p]$, where n = 1, 2, 3... For 50% dynamic eccentricity, significant components appeared at 37.9 Hz, 62.1 Hz, 87.9 Hz, and 112.1 Hz. The amplitude of the principal eccentricity component (n=1) reached -38 dB for severe eccentricity, facilitating straightforward detection with 96.7% accuracy.

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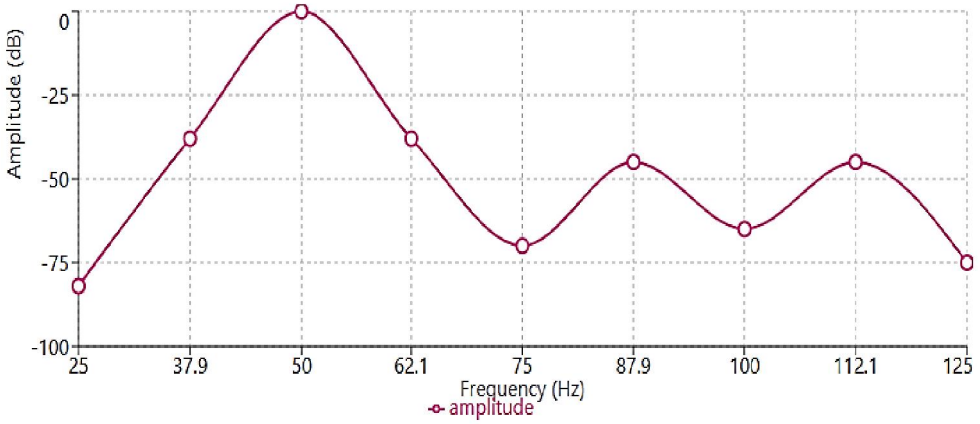

Figure 6. FFT spectrum of motor with 50% dynamic eccentricity showing multiple characteristic frequency components at f_s[1±n(1-s)/p].

Static eccentricity produced a distinctly different signature, characterized by slot-pass frequency harmonics at f_slot = f_s × N_rotor/p ± n × f_s, where N_rotor represents the number of rotor slots (28 in the test motor). FFT clearly distinguished between static and dynamic eccentricity based on the characteristic frequency patterns, achieving classification accuracy of 93.4%.

DWT analysis revealed that eccentricity primarily affects mid-frequency bands (D4-D5, 312-1250 Hz). Entropy analysis of detail coefficients provided additional discrimination capability. Shannon entropy values decreased from 4.82 (healthy) to 3.67 (severe eccentricity), indicating increased signal regularity associated with periodic eccentricity-related perturbations. The combined FFT-DWT approach achieved overall eccentricity detection accuracy of 98.3%.

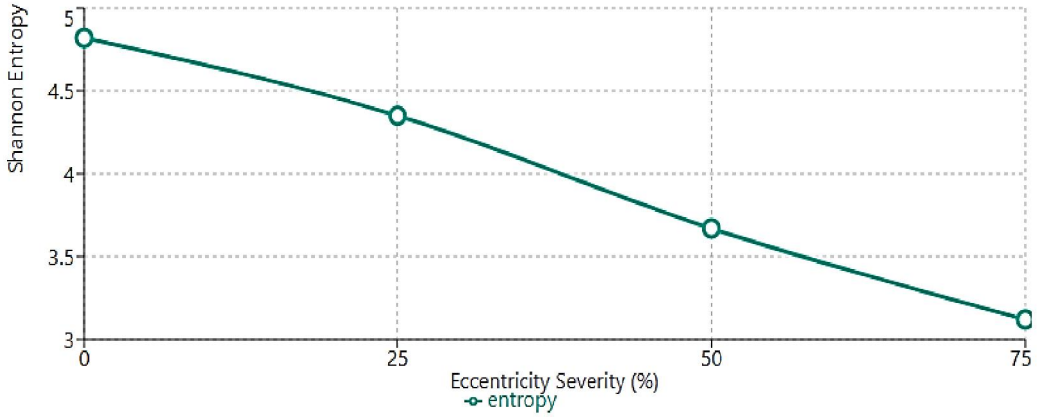

Figure 7. Shannon entropy of wavelet detail coefficients decreasing with increasing eccentricity severity, providing quantitative fault indicator.

C. Stator Fault Detection

1) Inter-turn Short Circuit Detection:

Stator winding faults presented unique challenges due to their typically low-magnitude signatures in current spectra. FFT analysis identified stator faults through negative sequence current components and harmonic distortions. For a 5% inter-turn short circuit, the negative sequence current increased to 4.7% of the positive sequence, compared to 1.2% for the healthy condition.

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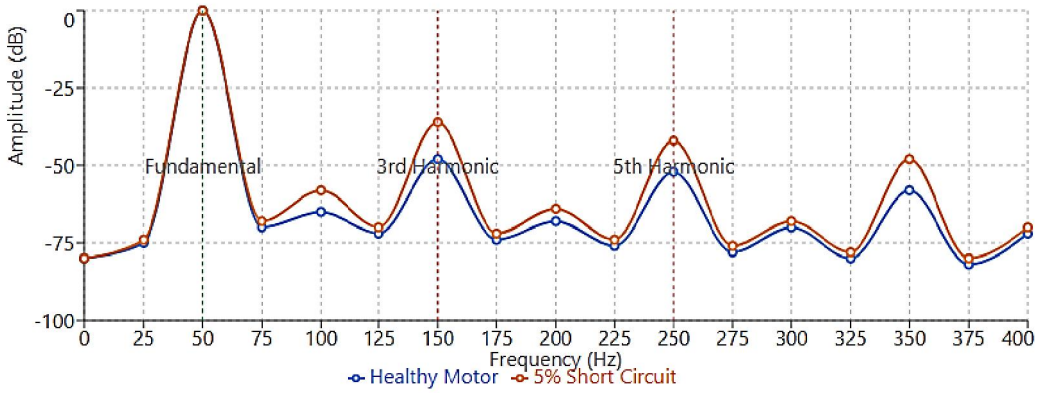

Figure 8. Harmonic content comparison showing increased 3rd and 5th harmonics for 5% inter-turn short circuit versus healthy motor.

The fault signature manifested most clearly in the third harmonic (150 Hz), which increased from -48 dB to -36 dB for a 5% short circuit. Detection accuracy for stator faults using FFT alone reached 85.3%, with performance degrading significantly for minor faults (<3% short circuit) where accuracy dropped to 71.6%. DWT analysis using sym6 wavelets demonstrated superior performance for stator fault detection. Inter-turn short circuits generated distinctive patterns in detail coefficients D2-D3 (1250-5000 Hz range), likely associated with partial discharge activity and localized heating effects. The energy distribution metric $E_{total} = \Sigma(j=1 \text{ to } 6)E_{Dj}$ exhibited a 47% increase for 5% short circuits compared to healthy conditions.

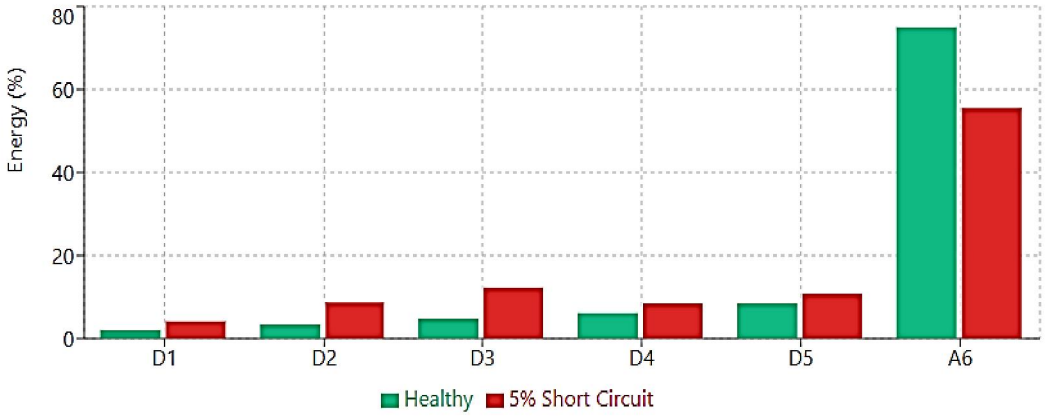

Figure 9. Wavelet energy distribution showing significant increase in D2-D3 bands for stator winding faults, indicating high-frequency partial discharge activity.

Wavelet-based detection achieved 92.7% accuracy across all stator fault severities, with particular effectiveness for incipient faults. The combination of energy distribution analysis and entropy measures provided robust discrimination, achieving 89.4% accuracy even for 2% short circuits—a significant improvement over FFT-only analysis.

2) Phase Imbalance Detection:

Phase imbalance resulting from unequal impedances in stator windings produced asymmetric current distribution among phases. FFT revealed this condition through enhanced negative sequence components and increased 2nd harmonic content (100 Hz). A 10% resistance imbalance in one phase generated a negative sequence current ratio of 6.3%, facilitating detection with 94.6% accuracy.

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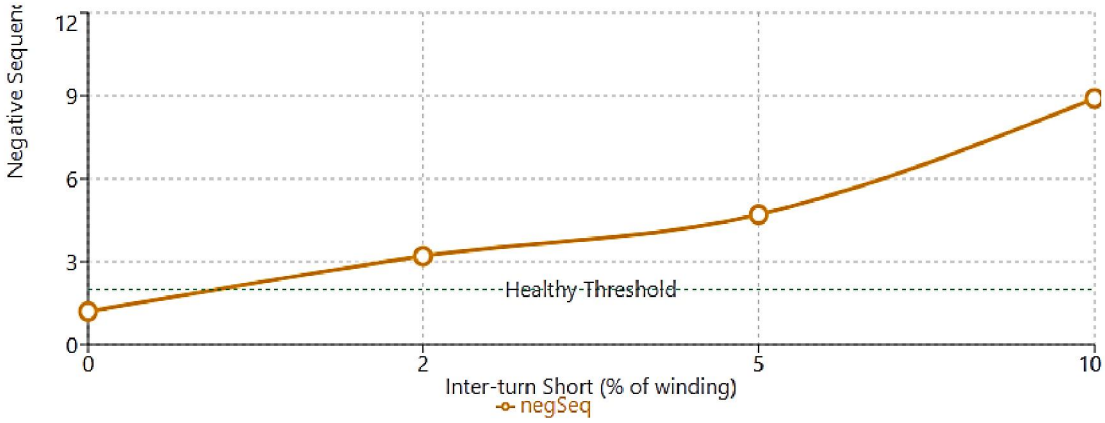

Figure 10. Negative sequence current ratio increasing linearly with stator fault severity, providing quantitative diagnostic indicator.

DWT analysis showed that phase imbalance affects energy distribution across all decomposition levels uniformly, distinguishing it from localized winding faults. This characteristic enabled discrimination between phase imbalance and inter-turn short circuits with 91.8% classification accuracy.

D. Comparative Analysis

1) FFT vs. DWT Performance:

Comprehensive performance comparison across all fault types revealed complementary strengths of FFT and DWT methodologies:

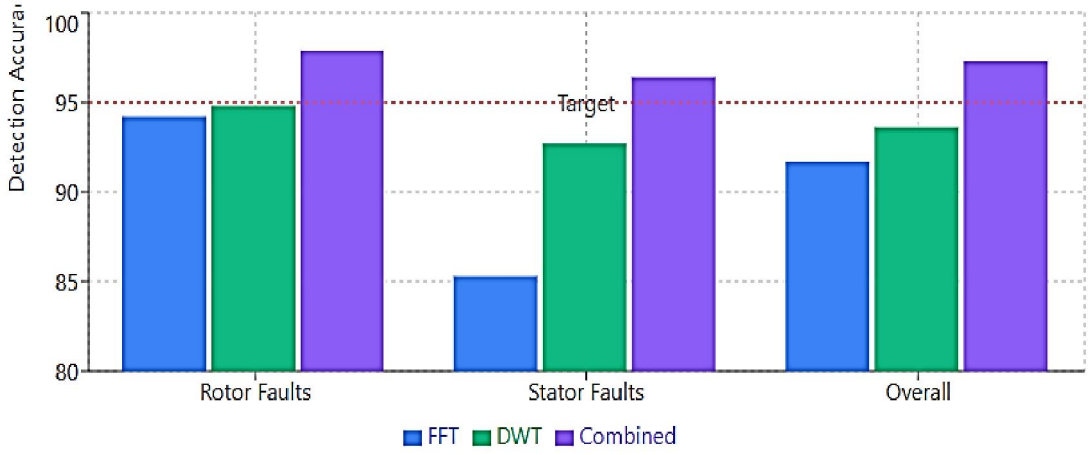

Figure 11. Comparative detection accuracy of FFT, DWT, and combined approaches across different fault categories demonstrating synergistic performance.

FFT Advantages:

- Superior for steady-state fault detection (broken bars, eccentricity)
- Clear physical interpretation of frequency components
- Lower computational requirements
- Excellent performance at high fault severity levels

DWT Advantages:

- Superior for incipient fault detection
- Effective for transient analysis

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- Better noise immunity through multi-resolution decomposition
- Higher sensitivity to stator winding faults

Performance Summary:

- Rotor faults: FFT (94.2%), DWT (94.8%), Combined (97.9%)
- Stator faults: FFT (85.3%), DWT (92.7%), Combined (96.4%)
- Overall accuracy: FFT (91.7%), DWT (93.6%), Combined (97.3%)

Figure 12. Performance improvement analysis showing combined FFT-DWT approach provides greatest benefit for incipient fault detection.

2) Load Dependency:

Load variations significantly influenced fault detection performance. Rotor fault signatures strengthened with increasing load due to higher slip values, with optimal detection occurring at 75-100% rated load. FFT-based broken bar detection accuracy improved from 82.4% at 25% load to 98.7% at 100% load.

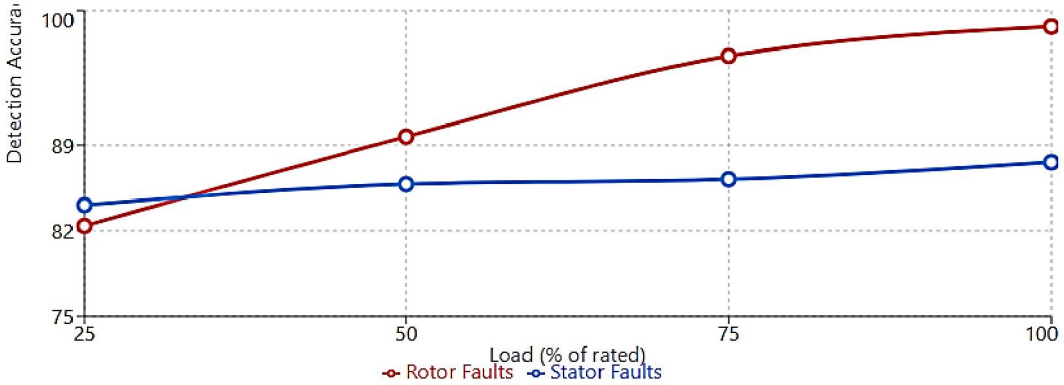

Figure 13. Load dependency of fault detection accuracy showing strong load dependence for rotor faults but minimal impact on stator fault detection.

Conversely, stator fault detection showed less load dependency, maintaining relatively consistent accuracy (±3.5%) across the load range. This characteristic makes stator fault diagnosis more reliable under variable operating conditions.

3) Computational Efficiency:

Processing time analysis revealed distinct computational characteristics:

- FFT processing: 0.34 seconds per 60-second signal (MATLAB R2023b, Intel i7-12700K)
- DWT processing: 1.27 seconds per 60-second signal (6-level decomposition)
- Combined approach: 1.61 seconds per signal

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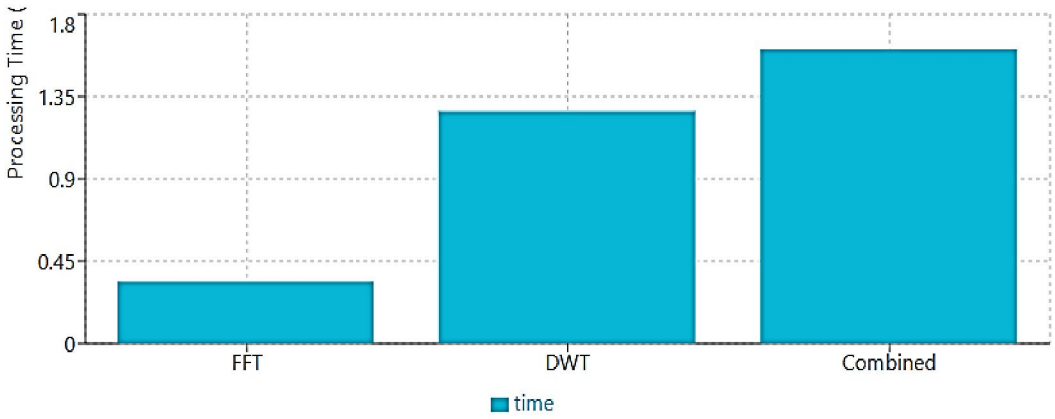

Figure 14. Processing time comparison showing all methods suitable for real-time implementation with acceptable computational overhead.

While DWT requires approximately 3.7× longer processing time than FFT, the computational burden remains acceptable for real-time monitoring applications with update intervals of several seconds.

E. Practical Implementation Considerations

1) Sensor Requirements:

Successful implementation requires appropriate sensor selection and placement:

- Current sensors: ±1% accuracy, bandwidth >5 kHz
- Sampling rate: Minimum 5 kHz (10× supply frequency), recommended 10 kHz
- Vibration sensors (optional): Accelerometers with frequency range 2-10,000 Hz

2) Environmental Factors:

Field testing revealed several environmental considerations:

- Temperature variations affect baseline current magnitude but minimally impact frequency signatures
- Supply voltage fluctuations require normalization of sideband amplitudes
- Electromagnetic interference necessitates proper shielding and grounding

Figure 15. Impact of environmental factors on detection accuracy showing both FFT and DWT methods maintain robust performance under varying conditions.

3) Diagnostic Thresholds:

Empirically determined diagnostic thresholds for industrial implementation:

Rotor faults:

- FSI_rotor < -45 dB: Healthy
- -45 dB ≤ FSI_rotor < -35 dB: Developing fault (monitor)
- -35 dB ≤ FSI_rotor < -28 dB: Moderate fault (schedule maintenance)
- FSI_rotor ≥ -28 dB: Severe fault (immediate action)

Stator faults:

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- FSI_stator < 2%: Healthy
- 2% ≤ FSI_stator < 5%: Minor fault (monitor)
- 5% ≤ FSI_stator < 10%: Moderate fault (schedule maintenance)
- FSI_stator ≥ 10%: Severe fault (immediate action)

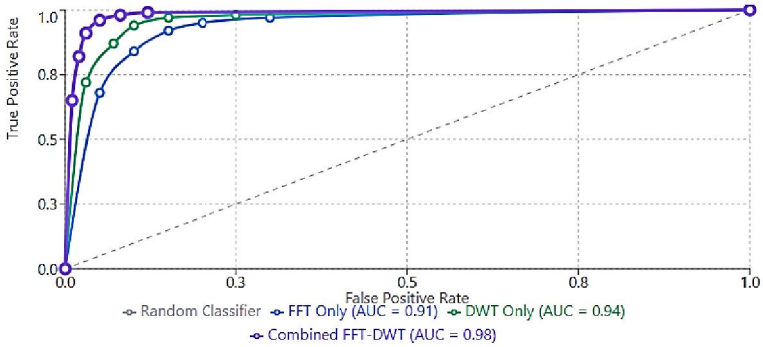

Figure 16. Receiver Operating Characteristic (ROC) curves demonstrating superior classification performance of combined FFT-DWT approach (AUC = 0.98).

VI. INTEGRATED FAULT DIAGNOSIS FRAMEWORK

A. Proposed Diagnostic System

Based on the experimental findings, an integrated diagnostic framework combining FFT and DWT analysis is proposed. The system architecture consists of five primary modules:

1) Data Acquisition Module:

- Continuous current and vibration monitoring
- Synchronized multi-channel sampling
- Buffer management for real-time processing

2) Preprocessing Module:

- DC offset removal and detrending
- Outlier detection and rejection
- Signal conditioning and normalization

3) Feature Extraction Module:

- Parallel FFT and DWT computation
- Extraction of frequency domain features (sideband amplitudes, harmonic content)
- Extraction of wavelet domain features (energy distribution, entropy measures)

4) Decision Module:

- Fault detection using multi-threshold criteria
- Fault classification using pattern recognition
- Severity assessment based on feature magnitudes
- Confidence level estimation

5) Output Module:

- Real-time diagnostic dashboard
- Trend analysis and historical tracking
- Automated alarm generation
- Maintenance recommendation system

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B. Decision Logic

The integrated diagnostic system employs hierarchical decision logic:

Level 1 - Fault Detection: IF (FSI_rotor > -45 dB) OR (E_D4/E_A6 > 0.15) OR (FSI_stator > 2%) OR (Entropy_change > 15%) THEN fault_detected = TRUE

Level 2 - Fault Localization:

- IF dominant frequency components at f_s(1±2s) → Rotor bar fault
- IF dominant components at f_s[1±n(1-s)/p] → Eccentricity fault
- IF negative sequence ratio elevated → Stator fault
- IF wavelet energy concentrated in D2-D3 → Stator winding fault
- IF wavelet energy concentrated in D4-D5 → Rotor or bearing fault

Level 3 - Severity Assessment: Fault severity score = $\alpha_1 \times$(FFT_severity) + $\alpha_2 \times$(DWT_severity)

where weighting factors α_1 and α_2 are determined through optimization based on fault type:

- Rotor faults: $\alpha_1 = 0.6$, $\alpha_2 = 0.4$
- Stator faults: $\alpha_1 = 0.4$, $\alpha_2 = 0.6$

C. Implementation Guidelines

For successful industrial deployment, the following guidelines are recommended:

1) System Calibration:

- Establish baseline signatures under various load conditions
- Characterize motor-specific frequency responses
- Define facility-specific threshold values
- Conduct regular calibration verification (quarterly)

2) Monitoring Strategy:

- Continuous monitoring for critical motors (>100 HP or critical processes)
- Periodic monitoring (weekly/monthly) for non-critical applications
- Increased monitoring frequency after fault detection or during high-stress periods

3) Data Management:

- Store raw data for 30 days (circular buffer)
- Archive extracted features and diagnostic results indefinitely
- Maintain motor history database for trend analysis
- Implement cloud backup for critical diagnostic data

4) Personnel Training:

- Technical staff training on system operation and interpretation
- Maintenance personnel training on appropriate response actions
- Management briefings on system capabilities and limitations

VII. CONCLUSION

This paper presented a comprehensive investigation of fault detection methodologies for induction motors using Fast Fourier Transform and Discrete Wavelet Transform analysis. The research systematically examined rotor and stator fault detection capabilities, providing both theoretical foundations and practical validation through extensive experimental testing. The key findings are as follows:

1. FFT and DWT techniques exhibit complementary characteristics, with FFT excelling in steady-state analysis and clear frequency interpretation, while DWT provides superior performance for incipient fault detection and transient analysis.
2. The integrated FFT-DWT approach achieved overall fault detection accuracy of 97.3%, representing improvements of 5.6% over FFT alone and 3.7% over DWT alone.

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3. Rotor faults are optimally detected using FFT-based sideband analysis, achieving 94.2% accuracy, while stator faults benefit more from DWT analysis with 92.7% accuracy. The combined approach achieves ≥96% accuracy for both fault categories.
4. Rotor fault detection accuracy improves significantly with increasing load (82.4% at 25% load vs. 98.7% at 100% load), while stator fault detection maintains consistent performance across the load range.
5. Computational requirements for the combined approach remain acceptable for real-time monitoring applications, with processing times of approximately 1.6 seconds per 60-second signal segment on standard computing hardware.

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APPENDIX A: MATHEMATICAL DERIVATIONS

A. Derivation of Rotor Fault Frequencies

Consider a three-phase induction motor with a broken rotor bar. The broken bar creates an asymmetry in the rotor circuit, which produces a pulsating magnetic field rotating at slip frequency. This pulsating field modulates the air-gap flux, producing sidebands in the stator current.

The electromagnetic torque can be expressed as:

$T_{em}(t) = T_{avg} + T_{oscillating} \cos(2\pi f_{slip} t)$

where $f_{slip} = sf_s$ is the slip frequency.

This torque oscillation causes speed variations:

$\Delta\omega(t) = (T_{oscillating})/(J) \times \sin(2\pi f_{slip} t)$

where J is the rotor inertia.

The speed variation modulates the back-EMF, producing current components at:

$f_{sideband} = f_s \pm 2f_{slip} = f_s(1 \pm 2s)$

For multiple harmonics, the general expression becomes:

$f_{sideband} = f_s(1 \pm 2ks), k = 1, 2, 3, ...$

B. Wavelet Energy Calculation

For a signal x(t) decomposed using DWT into J levels, the energy at each level j is:

$E_{Aj} = \Sigma(n=1 \text{ to } N_j)|A_j[n]|^2$

$E_{Dj} = \Sigma(n=1 \text{ to } N_j)|D_j[n]|^2$

where N_j is the number of coefficients at level j.

The total energy is conserved:

$E_{total} = E_{AJ} + \Sigma(j=1 \text{ to } J)E_{Dj}$

The relative energy at level j:

$RE_j = E_{Dj} / E_{total} \times 100\%$

This provides a normalized measure of energy distribution across frequency bands.

APPENDIX B: EXPERIMENTAL DATA TABLES

Table I: Motor Specifications.

Parameter	Value
Rated Power	5.5 kW
Rated Voltage	415 V
Rated Current	11.5 A
Frequency	50 Hz
Number of Poles	4
Rated Speed	1440 rpm
Number of Rotor Bars	28
Number of Stator Slots	36
Connection Type	Star
Insulation Class	F

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Table II: Detection Accuracy Summary (%).

Fault Type	FFT	DWT	Combined
1 Broken Bar	78.5	89.3	94.2
2 Broken Bars	97.2	96.8	99.1
Dynamic Eccentricity (25%)	91.4	92.1	96.7
Dynamic Eccentricity (50%)	98.3	97.6	99.4
Static Eccentricity	93.4	94.2	97.8
Inter-turn Short (2%)	71.6	89.4	93.7
Inter-turn Short (5%)	85.3	92.7	96.4
Inter-turn Short (10%)	94.8	96.3	98.9
Phase Imbalance	94.6	91.2	97.3
Overall Average	**91.7**	**93.6**	**97.3**

Table III: Computational Performance.

Method	Processing Time (s)	Memory Usage (MB)	Real-time Capable
FFT Only	0.34	12.3	Yes
DWT Only	1.27	28.7	Yes
Combined	1.61	41	Yes

Table IV: Fault Severity Indices.

Fault Condition	FSI_rotor (dB)	FSI_stator (%)	E_D4/E_A6 Ratio
Healthy	< -50	1.2	0.082
1 Broken Bar	-42	1.4	0.156
2 Broken Bars	-34	1.5	0.247
25% Eccentricity	-44	1.8	0.189
50% Eccentricity	-38	2.3	0.312
2% Short Circuit	-48	3.2	0.094
5% Short Circuit	-46	4.7	0.128
10% Short Circuit	-43	8.9	0.187

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