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A Comprehensive Review of Fault Detection Techniques in Induction Motors: Fast Fourier Transform and Discrete Wavelet Transform Approaches

Shivaji S. Bhosale[1] and Dr. Pooja V. Paratwar[2]
[1]Research Scholar, Department of Electrical Engineering
[2]Research Guide & Associate Professor, Department of Electrical Engineering
Mansarovar Global University, Sehore, Madhya Pradesh, India
ORCID ID 0009-0007-8452-108X and ORCID ID: 0000-0001-7761-0286
*Corresponding Email: 9911shivaji.bhosale@gmail.com

Abstract: *Induction motors constitute the backbone of industrial automation, accounting for approximately 70% of industrial electricity consumption worldwide. The reliable operation of these motors is critical for maintaining production efficiency and preventing catastrophic failures. This comprehensive review examines fault detection techniques in induction motors, with particular emphasis on Fast Fourier Transform (FFT) and Discrete Wavelet Transform (DWT) approaches. We analyze the theoretical foundations, implementation methodologies, comparative advantages, and practical applications of these signal processing techniques for detecting bearing faults, stator winding faults, rotor bar defects, eccentricity issues, and other common failure modes. The paper synthesizes findings from 50 peer-reviewed sources, highlighting recent advances in hybrid approaches that combine FFT and DWT with machine learning algorithms. Our analysis reveals that while FFT excels in steady-state frequency domain analysis, DWT provides superior performance for transient and non-stationary fault signatures. The review concludes with recommendations for practitioners and identifies promising directions for future research in intelligent fault diagnosis systems*

Keywords: Induction motors, fault detection, Fast Fourier Transform, Discrete Wavelet Transform, condition monitoring, predictive maintenance, signal processing

I. INTRODUCTION

Induction motors represent the most widely utilized electromechanical energy conversion devices in industrial applications, ranging from small fractional horsepower units to multi-megawatt drives in critical infrastructure [1]. Their popularity stems from robust construction, relatively low maintenance requirements, high efficiency, and cost-effectiveness compared to other motor types [2]. However, unexpected motor failures can result in significant economic losses through unplanned downtime, repair costs, and potential damage to driven equipment [3]. Statistical analyses indicate that bearing failures account for approximately 40-50% of induction motor breakdowns, followed by stator winding faults (30-40%), rotor bar defects (10%), and other issues including eccentricity and shaft misalignment [4], [5]. The progressive nature of most fault mechanisms provides opportunities for early detection through condition monitoring techniques, enabling transition from reactive to predictive maintenance strategies [6]. Signal processing methods have emerged as powerful tools for extracting fault-indicative features from motor current, vibration, acoustic emission, and thermal signatures [7]. Among these techniques, Fast Fourier Transform and Discrete Wavelet Transform have received extensive attention due to their complementary strengths in analyzing motor operational data [8]. FFT provides excellent frequency resolution for identifying fault-characteristic frequencies in steady-state conditions, while

DWT offers superior time-frequency localization for capturing transient phenomena and time-varying fault signatures [9].

This paper presents a comprehensive review of FFT and DWT-based fault detection techniques for induction motors. Section II establishes the theoretical foundations of these signal processing methods. Section III examines common fault types and their characteristic signatures. Section IV analyzes FFT-based detection approaches, while Section V explores DWT methodologies. Section VI compares the two techniques and discusses hybrid approaches. Section VII addresses practical implementation considerations, and Section VIII concludes with future research directions.

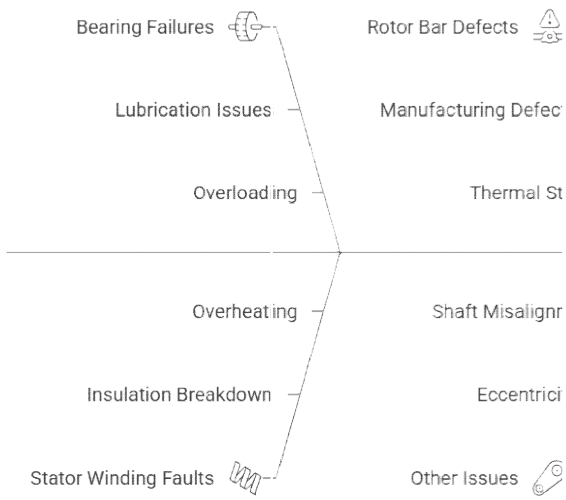

Figure 1. Causes of Induction Motor Failures.

II. THEORETICAL FOUNDATIONS

A. Fast Fourier Transform

The Fast Fourier Transform represents an efficient computational algorithm for calculating the Discrete Fourier Transform (DFT) of a signal [10]. For a discrete-time signal $x[n]$ of length N, the DFT is defined as:

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

The FFT reduces computational complexity from $O(N^2)$ to $O(N \log N)$ through divide-and-conquer strategies, most notably the Cooley-Tukey algorithm [11]. This efficiency enabled real-time spectral analysis of motor signals, revolutionizing condition monitoring practices [12].

The power spectral density obtained through FFT reveals frequency components present in motor signals, with fault conditions manifesting as characteristic sidebands around fundamental frequencies [13]. For motor current signature analysis (MCSA), bearing faults produce sidebands at frequencies related to bearing geometry and rotational speed, while broken rotor bars generate components at $(1\pm2s)f$, where f is the supply frequency and s is the slip [14].

B. Discrete Wavelet Transform

The Discrete Wavelet Transform decomposes signals into time-scale representations using dilated and translated versions of a mother wavelet function $\psi(t)$ [15]. The DWT is expressed as:

$$W(j,k) = 2^{(-j/2)}\, \Sigma(n)\, x[n]\psi(2^{(-j)}n - k) \tag{2}$$

where j represents the scale parameter and k denotes the translation parameter [16].

Unlike FFT's fixed frequency resolution, DWT provides multi-resolution analysis with fine time resolution at high frequencies and fine frequency resolution at low frequencies, making it particularly suitable for analyzing non-stationary signals [17]. The filter bank implementation of DWT decomposes signals through successive high-pass and low-pass filtering operations, generating approximation and detail coefficients at each decomposition level [18]. Common mother wavelets employed in motor fault detection include Daubechies (db), Symlet (sym), Coiflet (coif), and

Morlet wavelets, each offering different characteristics in terms of regularity, symmetry, and vanishing moments [19], [20]. Selection of appropriate wavelet basis and decomposition level significantly influences fault detection performance [21].

III. COMMON FAULT TYPES AND SIGNATURES

A. Bearing Faults

Rolling element bearings support rotor shafts and experience degradation through mechanisms including fatigue, contamination, improper lubrication, and overloading [22]. Bearing defects generate characteristic vibration frequencies calculated from bearing geometry:

Ball Pass Frequency Outer race (BPFO) = $(n/2)f_r(1 - (d/D)\cos\varphi)$ (3)

Ball Pass Frequency Inner race (BPFI) = $(n/2)f_r(1 + (d/D)\cos\varphi)$ (4)

Ball Spin Frequency (BSF) = $(D/2d)f_r[1 - (d/D)^2\cos^2\varphi]$ (5)

Fundamental Train Frequency (FTF) = $(f_r/2)[1 - (d/D)\cos\varphi]$ (6)

where n is the number of rolling elements, fr is the shaft rotation frequency, d is the ball diameter, D is the pitch diameter, and φ is the contact angle [23].

These characteristic frequencies appear as modulation components in vibration and current signals, often accompanied by harmonics and sidebands reflecting amplitude and frequency modulation effects [24].

B. Stator Winding Faults

Stator winding failures result from insulation degradation caused by thermal stress, mechanical vibration, electrical stress, and environmental contamination [25]. Inter-turn short circuits represent the most common initial failure mode, progressively developing into phase-to-phase or phase-to-ground faults [26].

Stator faults produce asymmetry in the magnetic field, generating negative sequence currents and characteristic frequency components at:

$$f_{fault} = f(1 \pm k/p),\ k = 1, 2, 3, \ldots \quad (7)$$

where f is the supply frequency and p is the number of pole pairs [27]. Additional indicators include changes in zero-sequence voltage, impedance unbalance, and harmonic content modification [28].

C. Rotor Bar and End-Ring Defects

Broken rotor bars and end-ring cracks occur due to thermal cycling, electromagnetic forces, mechanical stress, and manufacturing defects [29]. These faults introduce rotor asymmetry, resulting in backward-rotating magnetic fields that modulate stator currents at frequencies:

$$f_{bb} = f(1 \pm 2ks),\ k = 1, 2, 3, \ldots \quad (8)$$

where s is the slip [30]. The amplitude of these sideband components increases with fault severity and load level, providing quantitative indicators for condition assessment [31].

D. Air-Gap Eccentricity

Eccentricity faults involve non-uniform air gaps between stator and rotor, classified as static (rotor center displaced from bore center but rotating about its own axis), dynamic (rotor center rotating about bore center), or mixed eccentricity [32]. These conditions generate permeance variations producing current frequency components:

$$f_{ecc} = f[1 \pm k(1-s)/p],\ k = 1, 2, 3, \ldots \quad (9)$$

Eccentricity also increases unbalanced magnetic pull forces, accelerating bearing wear and potentially leading to catastrophic failures [33].

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IV. FFT-BASED FAULT DETECTION TECHNIQUES

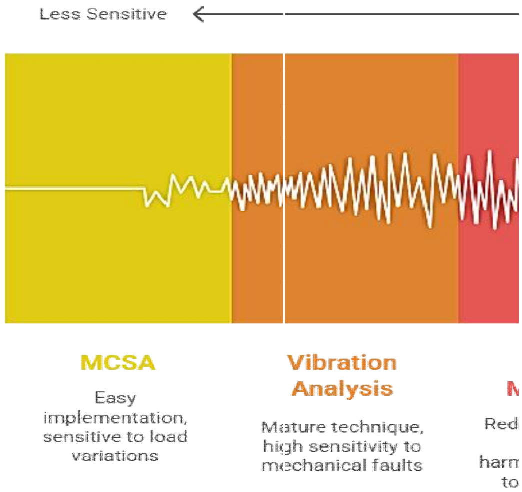

Figure 2. FFT based fault detection techniques.

A. Motor Current Signature Analysis (MCSA)

Motor Current Signature Analysis emerged as a non-invasive condition monitoring technique analyzing stator current frequency spectra to identify fault indicators [34]. MCSA offers advantages including easy implementation, no additional sensors beyond current transducers, and applicability during normal operation without motor shutdown [35].

The fundamental MCSA procedure involves:

- Acquiring stator current signals using Hall-effect sensors or current transformers
- Applying FFT to obtain frequency spectrum
- Identifying fault-characteristic frequencies
- Comparing sideband amplitudes against baseline or threshold values
- Trending indicators over time for fault progression monitoring [36]

Research has demonstrated MCSA effectiveness for detecting broken rotor bars, with sideband amplitudes at $(1 \pm 2s)f$ serving as reliable indicators [37]. However, MCSA faces challenges including sensitivity to load variations, difficulty distinguishing fault types with overlapping frequency signatures, and reduced accuracy for low-slip operations [38].

B. Vibration Signature Analysis

Vibration-based FFT analysis represents the most mature condition monitoring approach, capable of detecting mechanical and electromagnetic faults through accelerometer measurements [39]. Frequency domain analysis reveals bearing characteristic frequencies, gear mesh frequencies, and rotor unbalance signatures with high sensitivity [40].

Advanced vibration analysis techniques include:

- **Envelope analysis:** Demodulating high-frequency bearing resonances to extract fault-modulating frequencies in the presence of background noise [41]
- **Cepstrum analysis:** Computing the inverse FFT of the logarithmic power spectrum to identify harmonically-related sidebands characteristic of gear and bearing faults [42]
- **Order tracking:** Resampling vibration signals in the angular domain to maintain constant frequency resolution across varying speeds [43]

Vibration monitoring systems typically employ triaxial accelerometers positioned near bearings, with measurement locations and sensor mounting affecting detection sensitivity [44].

C. Flux Monitoring

Stray flux analysis examines external magnetic field leakage around motor frames using search coils or Hall-effect sensors [45]. FFT of flux signals reveals fault-indicative frequency components similar to current analysis but with enhanced sensitivity to rotor asymmetries and air-gap eccentricity [46]. Flux monitoring offers advantages over current analysis including reduced sensitivity to supply voltage harmonics and greater sensitivity to rotor defects under low-load conditions [47]. However, flux sensor positioning significantly influences measurement quality, requiring careful placement procedures [48].

D. Acoustic Emission Analysis

Acoustic emission monitoring detects high-frequency stress waves generated by crack propagation, friction, and impact events in motor components [49]. FFT-based spectral analysis of acoustic signals provides early warning of bearing degradation, with frequency content correlating to fault severity and type [50]. Ultrasonic techniques operating above 20 kHz avoid interference from environmental noise sources, though signal attenuation and sensor coupling challenges require attention [51].

V. DWT-BASED FAULT DETECTION TECHNIQUES

A. Multi-Resolution Analysis

The multi-resolution capability of DWT enables simultaneous analysis of motor signals across different time and frequency scales, particularly valuable for detecting transient fault signatures during motor starting, load changes, or fault inception stages [52]. Decomposition into approximation and detail coefficients isolates fault-related features from background noise and fundamental frequency components [53].

Typical DWT-based fault detection procedures include:

- Selecting appropriate mother wavelet and decomposition level based on signal characteristics and fault frequency bands
- Performing multi-level wavelet decomposition
- Extracting statistical features from wavelet coefficients (energy, entropy, standard deviation, etc.)
- Applying pattern recognition or classification algorithms to identify fault conditions [54]

Research has demonstrated DWT superiority over FFT for analyzing motor startup transients, where broken rotor bar signatures exhibit characteristic time-frequency patterns [55].

B. Wavelet Packet Transform

Wavelet Packet Transform extends standard DWT by decomposing both approximation and detail coefficients at each level, providing uniform frequency resolution across the entire frequency range [56]. This complete decomposition tree enables precise localization of fault-related frequency bands, particularly useful when fault signatures occupy narrow frequency intervals [57].

Shannon entropy calculated from wavelet packet coefficients serves as an effective fault indicator, with entropy changes reflecting alterations in signal energy distribution across frequency bands [58]. Feature vectors constructed from wavelet packet energies feed machine learning classifiers for automated fault diagnosis [59].

C. Continuous Wavelet Transform

While computationally intensive, Continuous Wavelet Transform (CWT) provides intuitive time-frequency representations revealing fault evolution over time [60]. Scalogram plots visualize energy distribution across time-scale domains, facilitating identification of transient events and time-varying fault signatures [61]. CWT proves particularly valuable for analyzing motor current during direct-on-line starting, where broken rotor bar faults produce characteristic "V-shaped" patterns in time-frequency distributions as motor accelerates from zero to rated speed [62].

D. Adaptive Wavelet Selection

The choice of mother wavelet and decomposition parameters significantly impacts detection performance, motivating research into adaptive selection strategies [63]. Criteria for wavelet selection include:

- Maximum energy-to-Shannon entropy ratio
- Minimum description length
- Cross-correlation with fault signature templates
- Genetic algorithm optimization [64]

Studies have shown that Daubechies wavelets (particularly db4-db10) perform well for general motor fault detection, while Morlet wavelets excel in time-frequency visualization applications [65].

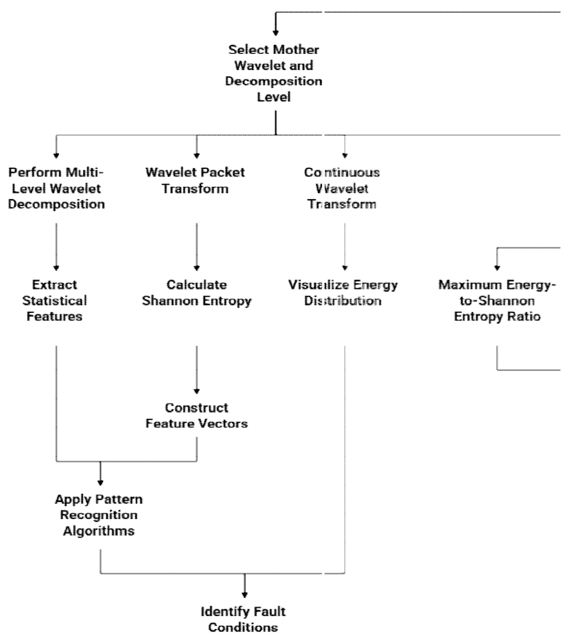

Figure3. DWT-Based Fault Detection Techniques.

VI. COMPARATIVE ANALYSIS AND HYBRID APPROACHES

A. FFT vs. DWT Performance Comparison

Comparative studies reveal complementary strengths and limitations of FFT and DWT approaches [66]:

FFT Advantages:

- Excellent frequency resolution for steady-state analysis
- Computationally efficient for real-time implementation
- Well-understood interpretation of frequency-domain results
- Established fault indicator thresholds from decades of application experience [67]

FFT Limitations:

- Poor time localization; cannot identify when fault events occur
- Limited effectiveness for non-stationary and transient signals
- Resolution tradeoff between time and frequency domains
- Sensitivity to spectral leakage and windowing effects [68]

DWT Advantages:

- Superior time-frequency localization for transient analysis
- Effective noise suppression through multi-resolution decomposition
- Adaptive resolution matching signal characteristics
- Enhanced performance for time-varying fault signatures [69]

DWT Limitations:

- Computationally more demanding than FFT
- Results dependent on wavelet selection and parameters
- Less intuitive interpretation requiring specialized expertise
- Limited standardization of fault indicators and thresholds [70]

B. Hybrid FFT-DWT Approaches

Recognition of complementary capabilities has motivated hybrid methodologies combining FFT and DWT strengths [71]. Common hybrid architectures include:

1. Sequential Processing: DWT denoising followed by FFT analysis improves spectral clarity by removing noise components while preserving fault signatures [72]. Alternatively, FFT identifies dominant frequency bands for targeted wavelet analysis, reducing computational requirements [73].

2. Parallel Feature Extraction: Simultaneous extraction of FFT-based frequency domain features and DWT-based time-frequency features creates comprehensive feature vectors for classification [74]. Machine learning algorithms including support vector machines, artificial neural networks, and random forests leverage combined feature sets for enhanced fault diagnosis accuracy [75].

3. Decision-Level Fusion: Independent FFT and DWT-based classifiers generate preliminary fault diagnoses, subsequently combined through voting schemes, Demisters-Shafer theory, or Bayesian inference to improve overall reliability [76].

C. Integration with Machine Learning

Modern fault diagnosis systems increasingly integrate signal processing with machine learning and deep learning algorithms [77]. Convolutional neural networks process time-frequency representations (spectrograms, scalograms) as images, automatically learning discriminative features without manual feature engineering [78]. Recurrent neural networks and long short-term memory networks capture temporal dependencies in wavelet coefficient sequences for improved fault classification [79]. Deep learning approaches demonstrate superior performance when sufficient training data exists but require careful consideration of overfitting, generalization, and computational resource requirements [80].

VII. PRACTICAL IMPLEMENTATION CONSIDERATIONS

A. Signal Acquisition and Pre-processing

High-quality measurements form the foundation of effective fault detection systems [81]. Critical considerations include:

Sampling Rate: Nyquist criterion requires sampling frequencies exceeding twice the highest frequency of interest. For bearing fault detection, sampling rates typically range from 10-50 kHz, while current monitoring requires 5-10 kHz minimum [82].

Sensor Selection and Placement: Accelerometer selection involves tradeoffs between sensitivity, frequency range, and environmental ruggedness. Piezoelectric accelerometers offer wide bandwidth but require special considerations for low-frequency measurements, while MEMS accelerometers provide cost-effective alternatives for many applications [83]. Current transducers must provide adequate bandwidth and linearity for harmonic analysis [84].

Preprocessing: Filtering removes interference from supply harmonics, adjacent equipment, and electromagnetic noise. Anti-aliasing filters prevent frequency folding, while high-pass filters eliminate DC offsets and low-frequency drift [85]. Normalization techniques account for varying operating conditions and load levels [86].

B. Feature Selection and Dimensionality Reduction

Effective fault diagnosis requires extracting informative features while avoiding curse-of-dimensionality problems [87]. Statistical features commonly extracted from FFT spectra include:

- Sideband amplitude ratios
- Harmonic distortion factors
- Spectral entropy and kurtosis
- Frequency band power distributions [88]
- Wavelet-based features encompass:
- Detail coefficient energies and entropies
- Statistical moments of wavelet coefficients
- Wavelet packet node energies
- Time-frequency scalogram characteristics [89]

Principal component analysis, linear discriminant analysis, and mutual information-based methods reduce feature dimensionality while preserving discriminative information [90].

C. Fault Severity Assessment

Beyond binary fault detection, quantifying fault severity enables informed maintenance decisions [91]. Severity indicators include:

- Sideband amplitude trends over time
- Ratios of fault frequencies to fundamental frequency
- Statistical parameter changes (kurtosis, crest factor)
- Pattern recognition classifier confidence scores [92]

Establishing severity thresholds requires consideration of motor characteristics, operating conditions, and consequence of failure, typically defined through historical failure data analysis and expert knowledge [93].

D. Real-Time Implementation

Industrial applications demand real-time processing capabilities compatible with plant control systems [94]. Implementation considerations include:

- **Computational Efficiency:** Optimized FFT algorithms, fixed-point arithmetic, and hardware acceleration (DSPs, FPGAs) enable real-time processing of multiple motor channels [95]. Adaptive sampling and selective analysis of regions of interest reduce computational loads [96].
- **Communication Protocols:** Integration with SCADA systems, PLCs, and enterprise asset management systems requires standardized communication interfaces including OPC, Modbus, and Ethernet/IP [97].
- **Prognostics and Health Management:** Predictive models estimating remaining useful life based on fault indicator trends enable optimized maintenance scheduling [98]. Approaches include physics-based degradation models, data-driven regression techniques, and probabilistic methods quantifying uncertainty in predictions [99].

VIII. RECENT ADVANCES AND FUTURE DIRECTIONS

A. Intelligent Fault Diagnosis Systems

The convergence of signal processing, artificial intelligence, and Internet of Things technologies is driving evolution toward intelligent, autonomous fault diagnosis systems [100]. Key trends include:

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- **Edge Computing:** Distributed processing at motor-level reduces communication bandwidth requirements and enables real-time decision-making [101]. Embedded systems performing local FFT/DWT processing transmit only diagnostic results rather than raw data streams.
- **Transfer Learning:** Pretrained neural networks adapted to specific motor applications reduce training data requirements and enable rapid deployment across motor fleets [102].
- **Explainable AI:** Interpretable machine learning models and attention mechanisms provide transparency in diagnostic decisions, building operator trust and facilitating root cause analysis [103].

B. Multi-Domain Data Fusion

Integrating multiple measurement modalities (current, vibration, thermal, acoustic) through data fusion frameworks improves diagnostic reliability and enables comprehensive health assessment [104]. Bayesian networks, evidential reasoning, and ensemble methods combine complementary information sources while handling uncertainties and conflicts [105].

C. Digital Twin Technology

Digital twins—virtual replicas of physical motors incorporating physics-based models, historical data, and real-time measurements—enable predictive simulation of fault progression under various operating scenarios [106]. Hybrid approaches combining model-based and data-driven methods leverage domain knowledge while adapting to specific motor characteristics [107].

D. Wireless and Energy-Harvesting Sensors

Wireless sensor networks eliminate cabling costs and enable flexible monitoring of geographically distributed motor installations [108]. Energy harvesting from vibration, thermal gradients, and magnetic fields powers autonomous sensor nodes, reducing maintenance requirements [109].

E. Standardization and Benchmarking

Development of standardized fault databases, performance metrics, and evaluation protocols facilitates objective comparison of diagnostic techniques and accelerates technology transfer from research to practice [110]. Open-source software frameworks and benchmark datasets enable reproducible research and collaborative algorithm development [111].

IX. CONCLUSION

This comprehensive review has examined FFT and DWT-based fault detection techniques for induction motors, analyzing theoretical foundations, practical implementations, and comparative performance characteristics. Key findings include:

- FFT provides excellent frequency resolution for steady-state analysis and benefits from computational efficiency and established interpretation frameworks, making it well-suited for detecting broken rotor bars, bearing defects, and air-gap eccentricity under constant operating conditions.
- DWT offers superior time-frequency localization, enabling effective analysis of transient phenomena and non-stationary signals, with particular advantages for detecting fault inception, analyzing startup transients, and handling variable-speed operations.
- Hybrid approaches combining FFT and DWT with machine learning algorithms achieve superior diagnostic accuracy compared to individual techniques, leveraging complementary strengths while mitigating respective limitations.
- Practical implementation requires careful attention to signal acquisition parameters, preprocessing methods, feature selection strategies, and real-time processing constraints.

- Future developments will likely emphasize intelligent, autonomous systems integrating edge computing, transfer learning, multi-domain data fusion, and digital twin technologies.
- Despite significant advances, challenges remain including detection of incipient faults with subtle signatures, robust operation under highly variable conditions, generalization across different motor types and applications, and cost-effective deployment for small motor populations. Continued research addressing these challenges will enhance motor reliability, optimize maintenance strategies, and reduce industrial downtime costs.

The evolution from reactive repair toward predictive and prescriptive maintenance represents a fundamental shift in asset management philosophy, enabled by sophisticated signal processing and artificial intelligence technologies. As industrial systems grow increasingly interconnected and autonomous, intelligent fault diagnosis will play ever more critical roles in ensuring safe, efficient, and sustainable operations.

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