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Multi-Resolution Analysis for Induction Motor Health Assessment: A Review Approach

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Abstract

Recently, multiresolution analysis (MRA) techniques have been introduced into the field of condition monitoring and fault diagnosis of induction motors, which made valuable steps towards being able to operate signals on different time-frequency scales at the same time. This systematic review focuses on the latest literature trends of MRA-based methods used in induction motor health assessment, particularly wavelet transforms, empirical mode decomposition (EMD), variational mode decomposition (VMD), and several hybrid techniques. The efficiency of these methods in the presence of bearing defects, stator winding faults, rotor bar breaks, or eccentricity is analysed in this paper. The review also considers signal acquisition processes, feature extraction techniques, and classification algorithms de rigueur for diagnostic systems based on MRA. Identifies current limitations and suggests future research paths, which include integrating AI, IoT-based monitoring systems, and signal processing. This paper is a reference material for researchers and practitioners on induction motor CM.

Keywords: *Induction motor, multiresolution analysis, wavelet transform, condition monitoring, fault diagnosis, predictive maintenance*

I. INTRODUCTION

Induction motors are the lifeblood of contemporary industrial systems, driving everything from manufacturing machines to heating, ventilation, and air-conditioning (HVAC) plants. This popularity is mainly due to their rugged construction, high operational efficiency, and low maintenance demands compared to other motors. Nevertheless, unpredictable motor breakdowns can lead to devastating financial losses, as an in-depth report disclosed that unscheduled downtime might cost industrial plants tens of thousands of dollars for every hour lost, thereby directly and detrimentally affecting overall productivity and profitability [1]. In response to the importance of motor reliability, efforts have increasingly been made to develop more advanced methods for condition monitoring and fault diagnosis that would allow predictive maintenance strategies. Conventional motor monitoring methods are based on one-dimensional analysis techniques, which might not measure the various fault-related phenomena in a multiscale manner. However, these traditional approaches often fail to detect nuanced early warning signs of impending failures, manifesting across different frequency bands and timescales. Multiresolution analysis (MRA) overcomes these key limitations as it can provide time and frequency domain information at various scales, and hence is ideal for analyzing the non-stationary signals typically associated with motor faults [2]. Significant advancements in digital signal and computational processing power have fueled the evolution of MRA techniques. Semi-late pioneering work in the 1980s and 1990s, early wavelet analysis theory, and more recent methods such as empirical mode decomposition (EMD) [3] and variational model desild compound disassembly VMD have emerged over time [4]. Given that advanced signal processing techniques can uncover transient phenomena and extract relevant features from complicated vibration and current signatures, these have been widely used for motor fault diagnosis. As such, bringing MRA with the modern machine learning algorithms has created an environment where the automated fault detection and classification system can be implemented and handled much more reliably, leading towards a more reliable and accurate diagnostic system. A schematic system of multiresolution analysis for motor fault diagnosis is presented in Figure 1.

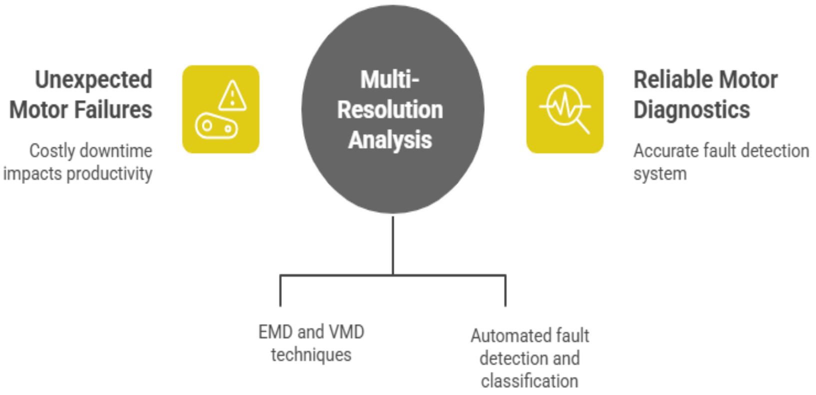

Figure 1. Multiresolution Analysis for Motor Fault Diagnosis.

II. FUNDAMENTALS OF MULTIRESOLUTION ANALYSIS

A. Theoretical Background

The bespoke mathematical framework that encompasses the analysis of signals at multiple scales together is known as Multiresolution analysis. In 1989, Mallat introduced this concept formally, stating that MRA could be realized computationally efficiently using well-defined filter bank structures [1]. The basic idea behind wavelet analysis is to break a signal into approximation and detail coefficients across different scales, in which approximation coefficients correspond to lower frequency components reflecting the structure of the signal. In contrast, detailed ones carry fast oscillating variations that encode transient information. For a given continuous signal f(t), the MRA decomposition can be mathematically expressed as:

$$f(t) = \Sigma c_{j,k} \varphi_{j,k}(t) + \Sigma \Sigma d_{j,k} \psi_{j,k}(t)$$ **Eq.**1

Where $\varphi_{j,k}$ and $\psi_{j,k}$ represent scaling and wavelet functions, respectively, $c_{j,k}$ are approximation coefficients capturing the signal's low-frequency behavior, and $d_{j,k}$ are detail coefficients representing high-frequency transient components.

This mathematical framework allows for tracking a signal's properties through time-frequency space, providing knowledge impossible to obtain with techniques that would otherwise consider only parameters on a single resolution level.

B. Wavelet Transform Fundamentals

The continuous wavelet transform (CWT) of a signal f(t) is rigorously defined as:

$$CWT(a,b) = (1/\sqrt{a}) \int f(t) \psi^*((t-b)/a)\, dt$$ **Eq.**2

Where $\psi(t)$ represents the mother wavelet function, a is the scale parameter controlling frequency resolution, b is the translation parameter providing time localization, and * denotes complex conjugate operation. The discrete wavelet transform (DWT) provides a more computationally efficient implementation by strategically sampling the scale and translation parameters on a dyadic grid, significantly reducing computational complexity while preserving essential signal characteristics.

The most popular mother wavelets used in motor fault diagnosis are Daubechies wavelets (with excellent localization of both time and frequency), Morlet wavelets (ideal for analyzing oscillatory signals), Mexican hat wavelets (suitable for detecting transient effects), and Biorthogonal, as it provides guarantees for perfect reconstruction. The analysis results are directly affected by the selection of the mother wavelet and its criterion, including the nature of the fault signature, computational requirements, and desired time-frequency resolution.

III. INDUCTION MOTOR FAULT TYPES AND CHARACTERISTICS

A. Bearing Faults

One of the common failure modes in induction motors is bearing faults, which constitute about 40-50% of all motor failures for industrial applications [5]. These failures are observed as periodic impulses in vibration signals at frequencies closely related to bearing geometry and speed. The mathematical relationships for bearing fault characteristic frequencies are well-established:

Ball Pass Frequency Outer Race (BPFO): $f_r \times N_b \times (1 - d_b/D_p \times \cos(\alpha))/2$ **Eq.**3

Ball Pass Frequency Inner Race (BPFI): $f_r \times N_b \times (1 + d_b/D_p \times \cos(\alpha))/2$ **Eq.**4

Ball Spin Frequency (BSF): $f_r \times D_p/(2\times d_b) \times (1 - (d_b/D_p \times \cos(\alpha))^2)$ **Eq.**5

Fundamental Train Frequency (FTF): $f_r \times (1 - d_b/D_p \times \cos(\alpha))/2$ **Eq.**6

Where, f_r represents the rotor rotational frequency, N_b is the number of rolling elements, d_b is the ball diameter, D_p is the pitch diameter, and α is the contact angle.

These characteristic frequencies generate unique spectra that can be efficiently detected using MRA, especially when the bearing defects are incipient and produce weak impulsive responses.

B. Stator Winding Faults

Stator winding faults, including inter-turn short circuits, phase-to-phase faults, and phase-to-ground faults, indicate 30-40% of motor failures [6]. These faults produce important asymmetries in the stator magnetic field that consequently develop characteristic frequency components in the stator current spectrum. The primary fault indicators appear at specific frequencies:

$$f_{fault} = f_s \pm 2kf_r \qquad \textbf{Eq.}7$$

Where f_s represents the supply frequency, f_r is the rotor frequency, and k is a positive integer.
These have amplitude and phase characteristics corresponding to the winding on the stator, which is impressed by the fault severity and location.

C. Rotor Bar Faults

Broken rotor bars and end ring defects account for only about 5-10% of the average total motor failures, but if not detected, they can have serious operational consequences [7]. These faults introduce additional frequency components in the stator current spectrum at:

$$f_{fault} = f_s(1 \pm 2ks) \qquad \textbf{Eq.}8$$

Where s represents the motor slip and k is a positive integer.

Detection of these fault frequencies using spectral analysis is extremely high-resolution, especially under varying load conditions, where changes in slip can obscure the state of health signatures.

D. Eccentricity Faults

Eccentricity faults will appear when the rotor is not located at the center of the stator, with uneven air gap distribution [8]. Static eccentricity: A radial displacement, and Dynamic eccentricity: The Rotor is wobbling. Mixed eccentricity incorporates the two processes; thus, fault signatures become mixed. These faults give characteristic sidebands (around the fundamental and harmonics) with specific frequency characteristics dependent on the type and severity of eccentricity. Induction motor fault types are shown in Figure 2.

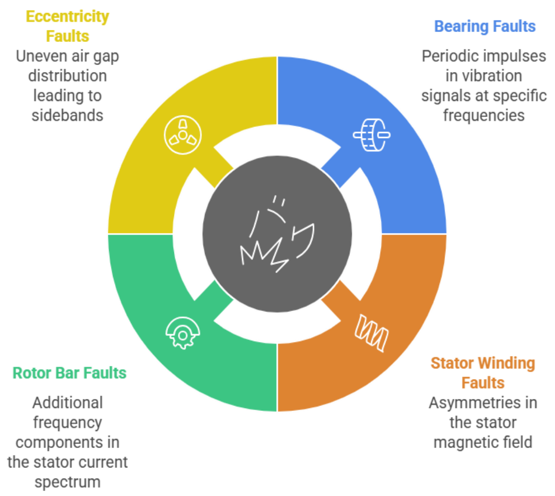

Figure 2. Induction Motor Fault Types.

IV. MULTIRESOLUTION ANALYSIS TECHNIQUES

A. Wavelet Transform Methods

(1) Continuous Wavelet Transform (CWT)

CWT has a good time-frequency resolution and has been widely used for motor fault diagnosis [9], which provides impressive properties. The method is exceptionally well-suited to analyzing motor signatures, with both transient and steady state components, as it can provide enhanced time resolution at high frequencies and good frequency resolution at low frequencies. Studies have shown it can detect the transient, subtle differences in the behavior of bearings with faults or other intermittent problems that conventional frequency domain analysis techniques might overlook.

(2) Discrete Wavelet Transform (DWT)

WPT is an extension of DWT, which offers frequency uniformity across all frequency bands (instead of the logarithmic splitting of standard DWT)[11]. This property is especially beneficial for such applications, where fault-related information can be partitioned between multiple frequency bands having similar significance. This technique has demonstrated great potential in complex motor systems with numerous simultaneous faults where different fault types may depend.

(3) Wavelet Packet Transform (WPT)

WPT extends the DWT concept by providing uniform frequency resolution across all frequency bands, rather than the logarithmic frequency division of standard DWT [11]. This characteristic makes it particularly useful for applications where fault-related information may be distributed across multiple frequency ranges with similar importance. The technique has shown significant promise in detecting multiple simultaneous faults in complex motor systems where different fault types may interact.

B. Empirical Mode Decomposition (EMD)

Huang et al. introduced EMD [10], a close approximation of Fourier analysis in the form of sparse Decomposition-based Representation (DR), 1998, which is a heavily data-driven method for signal decomposition in its nature [2]. It is based on the decomposition of the signals into intrinsic mode functions (IMFs) by examining local properties of the signal instead of just considering predefined basis functions. The adaptive nature of EMD makes it particularly attractive for analysis of non-stationary and nonlinear motor fault signatures that are not well approximated as linear combinations of predetermined point-symmetric mathematical models.

(1) Ensemble EMD (EEMD)

It is the mode mixing of the test data, which are decomposed using EMD, a common method named standard EMD, that causes this problem, and one way to speculatively recover some regularity is found in Ensemble Empirical Mode Decomposition (EEMD), which superimposes white noise to the input series before decomposition [12]. The approach applies EMD to the different noise-added signal copies and then averages those results to yield more robust, interpretable IMFs, thereby enhancing the efficacy of fault detection.

(2) Complete EEMD with Adaptive Noise (CEEMDAN)

CEEMDAN improves on EMD and EEMD by including the adaptive noise generated by each execution applied to the signal. This enhances progressive spectral separation between modes and minimizes the reconstruction error [13], making it more suitable for precision motor fault diagnosis.

C. Variational Mode Decomposition (VMD)

Dragomiretskiy and Zosso introduced VMD in 2014 as a variational optimization problem with the help of some constraints [3]. The procedure inherently identifies the number of modes (also center frequencies) that yield desired iterations and is comparatively much less susceptible to noise and sampling artifacts than its EMD-based alternatives. The VMD optimization problem is mathematically formulated as:

$$\min_{\{u_k\},\{\omega_k\}} \left\{\sum \left\| \partial_t\left[\left(\delta(t) + j/(\pi t)\right) * u_k(t)\right] e^{-j\omega_k t} \right\|^2\right\} \qquad \textbf{Eq.}9$$

subject to $\sum u_k = f(t)$

Where $\{u_k\}$ represents the set of decomposed modes, $\{\omega_k\}$ represents the corresponding set of center frequencies, and $\delta(t)$ is the Dirac distribution function.

D. Synchrosqueezing Transform

This approach increases the readability and accuracy of time-frequency representations by reassigning wavelet coefficients in a "smart" way to sharpen their frequency-localization aspect [14]. This method is found to be significantly beneficial for motor current signature analysis and suitable where the frequency localization needs to be precise for proper fault detection and classification. The multiresolution analysis techniques for motor fault diagnosis are shown in Figure 3.

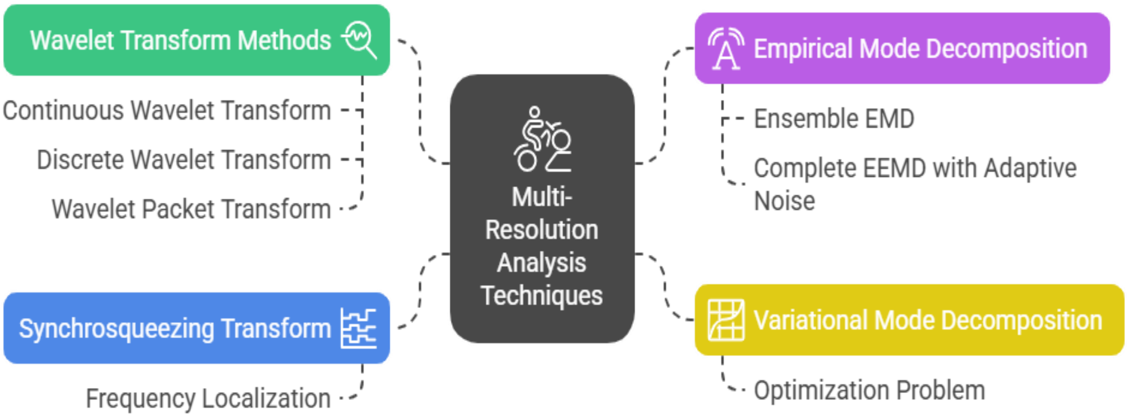

Figure 3. Multiresolution Analysis Techniques for Motor Fault Diagnosis.

V. SIGNAL ACQUISITION AND PREPROCESSING

A. Vibration Signal Analysis

Although it is supplanting some traditional methods, vibration monitoring is still the predominant method for a comprehensive motor condition diagnosis. Accelerometers mounted at (usual motor bearing housings) are generally placed on high-grade quality to give radial and axial components. Quality and reliability of the data critically depend on the choice of sensor location, mounting method, and frequency range. High-Resolution Analog-To-Digital Converters: Modern vibration monitoring systems use high-resolution analog-to-digital converters with virtually all of the state-of-the-art technology operating at a sampling rate between 25.6 kHz and 102.4 kHz (depending upon motor operational speed and expected fault frequency characteristics) to digitize the signals from full-bandwidth sensors located on the machine being monitored. One thing is to avoid spurious signal folding, which requires anti-aliasing filters from the input side of the Measurement until the end, where digital data is available.

B. Current Signature Analysis

The noninvasive viewpoint of MCSA when using current transformers or Hall effect sensors has many advantages [15]. However, it has been found to be a very sensitive method for certain rotor defects and some types of stator winding faults. The current signals are usually sampled between 5 kHz and 20 kHz, except for high-speed motors and when high-frequency fault components should be analysed.

C. Acoustic Emission Monitoring

Acoustic emission (AE) monitoring records the high stress waves resulting from the initiation and propagation of defects. Accelerometers (AE sensors) are typically in the frequency range of 100 kHz–1 MHz, which enables early warnings in incipient faults [16]. It involves thinking about how the sensor can be loaded inferiorly, how it is affected by environmental noise, and how it can be used without significant degradation of signals.

D. Thermal Monitoring

Infrared thermography and embedded temperature sensors provide information about motor thermal conditions and operational characteristics. Abnormal temperature patterns can indicate various fault conditions, including bearing degradation, stator winding problems, and cooling system failures, complementing other monitoring techniques. Figure 4 shows motor condition monitoring methods.

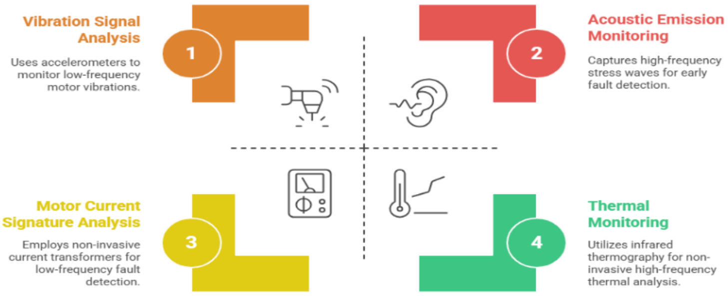

Figure 4. Motor Condition Monitoring Techniques.

VI. FEATURE EXTRACTION AND SELECTION

A. Time-Domain Features

Data available from infrared thermography and embedded temperature sensors is essential for gaining a clearer understanding of motor thermal conditions and operational characteristics. Different fault conditions like bearing degradation, stator winding problems, and cooling system failures are also typically associated with abnormal temperature patterns, so it is a good auxiliary monitoring technique. The most traditional time domain features include mean, variance, skewness, kurtosis, and fundamental statistics values like peak-to-peak value and root mean square(RMS) value. At the same time, they offer simple signal attributes that provide only a coarse representation of power quality health and robustness for early fault detection in complex industrial operating conditions.

The advanced time-domain features represent complicated statistical measures that capture various aspects of vibration and other diagnostic signals far more completely than basic statistical parameters, providing better sensitivity to diverse fault mechanisms. It is a basic impulsiveness indicator calculated by dividing the peak of the period by this value. It is particularly valuable for detecting impulsive signal characteristics like bearing faults, gear tooth damage, and similar defects. This metric is of particular significance in mechanical faults, as many types give rise to intermittent transients with a disproportionately high peak value increase and relatively small contribution to overall RMS levels. An increasing incidence of crest factor can indicate fault development at an early stage.

The shape factor (RMS divided by instantaneous mean absolute value) is used to determine the distribution of a signal and reproduce additional information about how energy within a time frame is distributed. The latter is beneficial for differentiating fault signatures since distinct mechanical faults generally affect the amplitude distribution of the signal in a specific manner [6]. A higher shape factor typically describes a distribution that is peakier about the mode location with rare large amplitude excursions, whereas lower shape factors are more uniform in nature.

The impulse factor generalizes the idea of peak and mean absolute value to create a quotient that more directly characterizes transient content in the signal compared with the crest factor. This measure shows very high sensitivity to shock-type events and transient phenomena typical of many mechanical faults, particularly those involving intermittent contact or impact mechanisms, such as bearing on a race defect or gear tooth chipping.

The margin factor offers increased fault detection sensitivity through an advanced normalization calculation, which is computed as the peak value divided by the mean of the magnitude of the signal. This formulation produces a metric that is particularly sensitive to very gradual changes in signal characteristics, which may be early signs of faults, and is valuable for early fault detection where subtle variations must be reliably detected amidst normal operational variability. The mathematical formulation of the margin factor generally leads to better fault diagnosis performance than other impulsiveness measures, particularly when the signatures of faults are only weakly visible or invisible below a certain level due to operational noise (or interference) components.

B. Frequency-Domain Features

This analysis laid down the characteristic fault frequencies and harmonic patterns required forfor accurate frequency domain diagnosis. The output includes spectral peaks of bearing fault frequencies, sideband patterns around supply frequency components, harmonic distortion indices, and some spectral entropy measures that would describe the distribution characteristics in the frequency domain.

C. Multiresolution Features

Features based on wavelets are one of the primary characteristics of multiresolution analysis and provide essential diagnostic information using various strategies. This distribution helps us understand how the signal energy is distributed in different frequency bands and decomposition levels, which would give some information about the changes in frequency content when dealing with varying fault conditions. Wavelet entropy measures a compendium of physiologic information signifying the signal's complexity by assessing the disorder and change in amplitude minute-to-minute that is often reflective of given fault expression [13]. Comparative metrics, in the form of relative wavelet energy ratios between frequency bands, demonstrate shifts in energy concentration from normal to faulty operating conditions of machines. Four new discriminative features, reflected skewness, varones, Skew2, sup, and Kurtosis, were extracted from the transformed feature space of detail coefficients at different decomposition levels for capturing the statistical characteristics of signal variations at various scales.

This EDM based feature type uses the adaptive decomposition energy property in empirical mode decomposition to reveal diagnostic characteristics from intrinsic mode functions. The energy distribution of these IMFs lets us know how the total signal energy is spread among various inherent modes. It thus provides fault-specific patterns in terms of variations of energy concentration across different oscillatory components. Variations of instantaneous frequency in each mode preserve the time-varying features that frequently emerge as a fault proceeds, which provide temporal information on how fault conditions evolve. Hilbert marginal spectrum characteristics provide improved diagnosticity by embedding complete time–frequency data to reflect the frequency content and how it changes throughout the signal. Cross-correlation between various IMFs indicates the coupling and interaction of different oscillating modes, clearly providing insight into complex fault mechanisms that combine simultaneous multiple frequencies. These VMD-based features can be helpful in condition monitoring applications because the variational mode decomposition allows for compact modes with clear spectral properties, which is ideal for fault diagnosis. Modal center frequency characteristics give exact details of dominant frequency contents inside each extracted mode, thereby allowing for capturing fault-specific frequency signatures that are hidden if observed in the original signal. On the other hand, bandwidth measures tell us how much one mode bands its frequency contents around its center frequency as trivial or compact modes, which could provide a discrimination among different mechanical faults with frequencies spreading in a non-uniform manner. Cross-correlation analysis among different modes shows the associations and influence between different frequency components, shedding light on how distinct dynamic behaviours of the system are correlated in normal and faulty conditions. Modal energy ratios play a key role in fault discrimination because they can quantify the significance of different frequency bands; thus, they form feature vectors well-suited for discerning between various fault types based on specific distribution patterns exhibited by the characteristic energy across these extracted modes.

D. Feature Selection Techniques

Accurate and reliable performance of these diagnostic systems in operation-critical applications across various industrial environments, operational conditions, levels of noise, and equipment configurations underscores the need for an effective feature selection. By selecting veterans, the high-dimensional feature spaces produced by multiresolution analysis techniques work well since only the most discriminative and stable features should weigh toward final diagnosis decisions. Feature Extraction and Selection Techniques are shown in Figure 5.

Figure 5. Feature Extraction and Selection Techniques.

Filter methods, on the other hand, are computationally independent of any learning algorithms and hence, can give a quick approximation of how well features individually contribute to the output. The correlation-based feature selection is a basic method to determine which features are highly correlated to others and, thus, unnecessary and can be removed, resulting in dimensionality reduction of the feature space while retaining relevant diagnostic information. Information gain measures provide a theoretically sound framework for quantifying feature importance in terms of the amount of fault class information each feature offers, and hence, allow the selection of features that optimise diagnostic performance overall. Relief algorithms help assess feature quality by scoring features over the instance space. They can differentiate nearby instances of different classes from each other, which is beneficial for diagnosing complex faults where decision boundaries may not be linear. Statistical significance tests protect the trustworthiness of features by using strict statistical standards to determine that the observed feature-target relationships are not due to random happenstance, thus facilitating more generalizable selected features across varying operational circumstances.

These methods are more exhaustive than filter methods because they approach the problem as a search over feature subsets, considering individual features and combinations of up to k, based on classifier-based performance of different limited groupings. Forward selection algorithms take an incremental approach to constructing the optimal feature set by starting from an empty set and incrementally adding features with the maximum increase in classification performance, thus ensuring added features contribute meaningful diagnostic information. Reverse in nature to forward techniques, backward elimination methods start with the complete feature set and remove features that seem less important for optimal classification performance, often yielding fewer features needed to achieve equivalent or better diagnosis accuracy. A selection of point-wise GA-based-selection techniques treat FP as an optimization issue and use evolutionary computation principles to explore feature combinations where greedy-type selection strategies could miss important information. Particle swarm optimization uses swarm intelligence to implement efficient and globally optimal heuristics for selecting a subset of features and proceeds with collective behavior from the group to navigate through a complex feature interaction landscape that separates true positive features from false positive suspect markers, streamlining them into high-performing diagnostic subsets.

With embedded methods, feature selection is automatically built into the learning algorithm during training, allowing these approaches to streamline feature selection and model parameters together. It is a type of regularization because of the L1 penalty term that LASSO imposes to drive the coefficients corresponding to irrelevant features (to some Degree) to zero, creating its own embedded method for feature selection. Ridge regression highlights multicollinearity issues resulting from high-dimensional feature spaces while protecting against overfitting by enforcing L2 regularization, preserving all features but reducing their coefficients. This enables elastic net methods to perform feature selection but also helps handle multicollinearity more successfully compared to L1 and L2 regularization on their own; this makes it particularly advantageous when dealing with challenging diagnostic problems involving highly correlated features. Feature importance: Statically, tree-based feature importance measures how much each feature contributes to reducing impurity in decision tree splits -- thereby providing a selection mechanism based on these values for which features to keep and remove -- thus yielding intuitive (interpretable) insights for maintenance personnel who can validate that this matches their domain preferences [2].

VII. CLASSIFICATION AND DIAGNOSTIC ALGORITHMS

A. Traditional Machine Learning Approaches

(1) Support Vector Machines (SVM)

SVMs perform favorably on motor fault classification tasks because of their effectiveness in high-dimensional feature spaces and strong generalization capabilities [17]. The kernel trick used in the method allows a nonlinear decision boundary to handle more complex fault diagnosis problems.

(2) Artificial Neural Networks (ANN)

Motor Fault Diagnosis References [18] have widely used multi-layer perceptrons and radial basis function networks. While some methods can learn complex nonlinear relationships between extracted features and fault conditions, overfitting often becomes an issue when training data is limited.

(3) k-Nearest Neighbors (k-NN)

K-NN is one of the simplest and most effective fault classification approaches. It uses feature similarity measures(background)[19]. The method's performance significantly relies on choosing suitable distance metrics and an optimal k for a given application task.

(4) Decision Trees and Random Forests

Tree-based methods provide highly interpretable decision rules and can appropriately account for numerical and categorical features [20]. In this case, such ensemble methods (random forests) make single decision trees obsolete by removing the overfitting concept.

B. Deep Learning Approaches

(1) Convolutional Neural Networks (CNN)

MRA techniques have performed outstandingly in processing time-frequency representations with CNNs [21]. Its automatic learning of hierarchical feature representations makes it particularly appealing for complex fault pattern recognition tasks as there is no or minimum requirement for manual feature engineering.

(2) Recurrent Neural Networks (RNN)

RNNs, especially Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) variants, are suitable for sequential data, which can capture the temporal dependencies in motor operational signature [22]. They are the best networks for analyzing time-series motor data in which temporal relationships matter most.

(3) Autoencoders

When trained in an unsupervised mode, autoencoders capture a compressed form of the typical motor operation pattern features that can be used to implement sophisticated anomaly detection based on reconstruction error analysis [23]. This is very useful, especially if we have little or no labelled fault data.

C. Ensemble Methods

Ensemble methods use many classification algorithms to enhance the productivity of diagnostic accuracy and robustness in the system. Sophisticated methods include bagging and boosting algorithms, third-layer stacking methods, weighted voting schemes, and multi-classifier fusion strategies that combine the power of different individual classifiers.

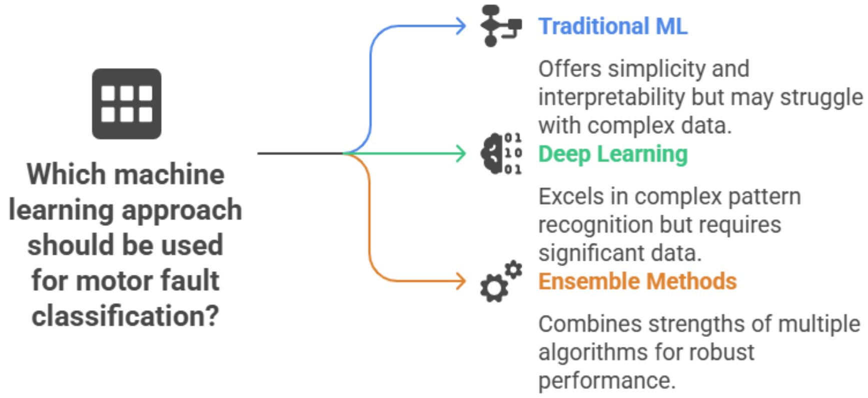

Figure 6. Machine Learning Approaches to Motor Fault Classification.

VIII. PERFORMANCE EVALUATION METRICS

A. Classification Metrics

The standard classification performance metrics offer extensive discrimination options to assess the performance of fault diagnosis systems over different diagnostic accuracies. Accuracy is the basis and is defined as the total number of correct classifications from all types of faults, representing a general measure of how well the system performs. Precision, which is calculated as true positives divided by the sum of true positives and false positives, expresses the ability of a system to not raise false alarms by examining how many optimistic predictions are correct. Recall or sensitivity, true positives / (true positives + false negatives), reflects the system's ability to classify all actual failures correctly but not misclassify critical issues. Specificity is similar; it works out true negatives over all actual negatives (true negatives + false positives). This evaluates the capacity of your system to acknowledge the typical work environment without issuing alarms when no violation occurs. It is a balanced way to assess the performance by computing the harmonic average of precision and recall; it gives just one metric by mending the requirement of minimizing false positives with the need to maximize fault detection rates, hence, it is beneficial for comparing several diagnostic approaches when there is about equal importance on both precision and recall.

B. Multi-Class Evaluation

Our evaluations show that metrics may be suitable for determining single fault diagnosis, but for complex multi-class fault diagnosis problems, more advanced evaluation metrics are needed to highlight the challenge of separating among various types of faults and operational conditions. Macro-averaged metrics are an unbiased assessment that calculates performance metrics for individual fault classes (potentially including positive and negative classes). This is then averaged to give a final score, where each fault type counts the same, irrespective of how many faults exist in the dataset. Considering all fault subclasses equally crucial from the diagnostic point of view is beneficial.

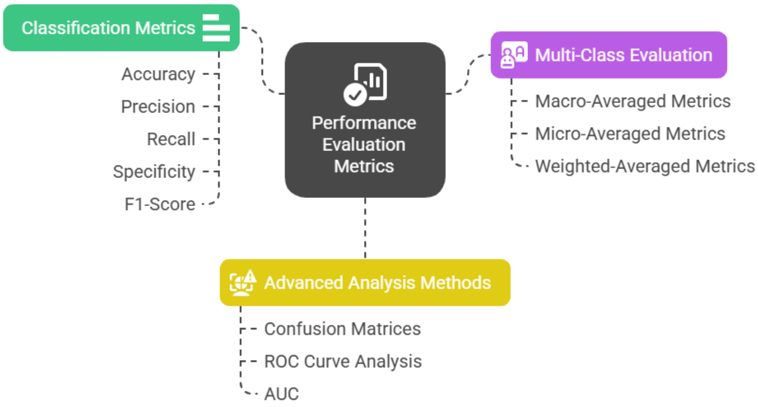

Figure 7. Performance Evaluation Metrics in Classification.

On the other hand, micro-averaged metrics calculate metrics globally by counting all samples from all classes. Therefore, it is more biased towards the dominant fault types (frequently occurring) when computing the overall performance assessment. This global count method is beneficial when the entire study aims to determine how well an overall system performs across all samples. Weighted-average metrics take an intermediate approach and compute performance metrics averaged over classes. Each class's contribution to the average is weighted by support, or the proportion of accurate labels corresponding to that class. This weighted aspect allows for a more realistic evaluation of system performance under real-world conditions where not all types of faults will occur with equal frequency, permitting the assessment to capture the practical reality that identifying common fault states is essential, but also needs to consider failure on rare but important modes.

C. Advanced Analysis Methods

The confusion matrices show where the algorithm consistently gets its classifications wrong and can help identify any systematic misclassification patterns about certain fault types. Receiver Operating Characteristic (ROC) curve analysis highlights the tradeoff between sensitivity and specificity over a range of decision thresholds. It provides a single overall Area Under the Curve (AUC) measure for comparing classifier performance.

X. CHALLENGES AND LIMITATIONS

A. Computational Complexity

Meanwhile, MRA methods, especially CWT and some advanced EMD-based methods, may be unsuitable for real-time monitoring systems with strict processing constraints due to their computational complexity. This tradeoff between analysis depth and processing speed is still a bottleneck for real industry applications that need immediate fault detection.

B. Parameter Selection

Most MRA techniques have various parameters that must be carefully tuned to work well across many dimensions. Intelligent choice of the wavelet type and the proper decomposition levels is necessary due to the varying nature of signal components at different frequency bands, directly affecting the method's efficiency. The mode extraction in EMD-based methods must be carefully tuned using stopping criteria and sifting parameters to avoid extracting more modes than exist in the signal (over-decomposition) or combining information about related sidebands/monochromatic components into fewer IMF modes.

Likewise, VMD implementations require a cautious choice of the number of extracted modes and the proper penalty factors to enforce the tradeoff between accuracy in decomposition and computational efficiency. The sophistication of these processes has led to automated parameter selection and optimization becoming broadly researched areas, with considerable algorithmic effort directed at minimizing manual tuning burden and increasing reliability and consistency of MRA method performance across varying signal types and applications.

C. Noise Sensitivity and Environmental Robustness

While MRA techniques generally provide good noise robustness compared to traditional methods, their performance can degrade significantly in high-noise industrial environments with electromagnetic interference, mechanical vibrations, and other disturbances. Advanced denoising strategies and robust feature extraction methods are essential to address these challenging operational conditions.

D. Interpretability and Explainability

Interpretability issues of the deep learning approaches for MRA-based fault diagnosis have become a bottleneck between powerful algorithmic capabilities and maintenance applications. It is difficult for maintenance personnel, who must act on the diagnosis towards the end of this chain, to comprehend why a complex neural network model produces specific outputs and understand how these outputs could be used in an automated decision-making system. This black box nature of deep learning models is especially troubling in safety-critical industrial applications, where not only are decisions based on fault detection required for regulatory compliance and ensuring safety, but also this discrepancy between the algorithmic sophistication and practical utility has underscored the essential interest of MRA-based diagnostic systems in developing explainable AI approaches. The proposed techniques would need to be able to generate human-interpretable explanations as to how multiresolution analysis features influence decisions from a fault classification perspective, such that maintenance teams can validate diagnostic outputs against domain knowledge and gain the trust necessary for the broad acceptance of AI-driven tools within industrial maintenance practices.

E. Data Requirements and Availability

The main problem of supervised learning-based approaches in fault diagnosis is the need for a large labeled dataset that covers almost all operating conditions and fault states. This is particularly the case for industrial settings where collecting these datasets is challenging, or expensive, and you need a lot of time to get all potential failure modes under different operating conditions. This issue in data collection is especially severe for rare fault types that only sporadically manifest during regular industrial operation but cause a lot of damage when they do. These rare yet crucial fault conditions are frequently underrepresented in training datasets. If the diagnostic systems are not well-trained with them, they could be ineffective at detecting exactly the failures that most jeopardize equipment safety and operational continuity. The average cost of setting up fault conditions intentionally for data collection is very high, both economically and logistically, and standard industrial operators have no incentive to disrupt usual production processes even for establishing an accurate representation of real-world faults, which further exacerbates the challenge of acquiring balanced inefficient datasets. Consequently, this limitation has led to greater exploration of other methods like unsupervised learning, transfer learning, and synthetic data generation approaches, which demonstrate potential in allowing us to overcome the limitations of having a small number of labeled fault data in real-world industrial setups.

XI. FUTURE RESEARCH DIRECTIONS

A. Integration with Artificial Intelligence

Subsequent work can examine new deep learning architectures tailored to MRA-based motor fault diagnosis, such as an attention mechanism for highlighting time-frequency areas of interest in constituent components, a graph neural network for capturing interactions between complex component behaviors, and a transformer architecture that can improve efficiency in processing long sequence data (motor signal). One of these examples is federated learning, which allows collaborative training of diagnostic models without compromising a company's proprietary information while maintaining critical data privacy and security constraints between different industrial facilities.

B. IoT and Edge Computing Integration

Advanced transfer learning techniques may minimize this data paucity issue in rare fault types where a few samples are labelled by developing highly sophisticated few-shot learning algorithms, which could be used for effective diagnosis based on raw images with minimum training examples. Specialized edge computing hardware advancements allow complex MRA algorithms to be pushed down to motor monitoring devices, significantly reducing communication latency and bandwidth requirements whilst enabling local real-time decision making. For example, implementing complex IoT network topologies could allow the integration of vibration, current, acoustic, and thermal sensor modalities to deliver a complete portrait of motor health vibrated from these different spectrums in unprecedented detail and accuracy. Fifth-generation (5G) wireless networks that provide high-speed but significantly low-latency allow the real-time transmission of high-resolution MRA data to central servers for processing, enabling more advanced diagnostic algorithms that may need considerable computing resources.

C. Advanced Signal Processing Techniques

In that respect, developing adaptive MRA techniques that self-adjust their parameters to better readapt themselves in changing operating conditions and signal characteristics may substantially enhance the diagnostic performance without demanding manual tuning or increasing operational complexity. New techniques for intelligent multimodal multiscale MRA information fusion may allow for robust and accurate fault diagnosis, especially in multi-failure situations. Recent advances in quantum computing technologies may provide new opportunities to revolutionize signal processing and pattern recognition approaches to motor fault diagnosis with orders of magnitude that increase processing speed and pattern recognition performance.

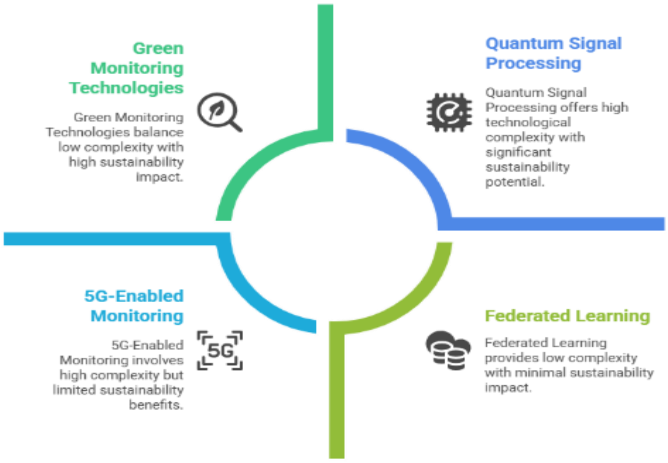

Figure 8. Future Research Directions.

D. Uncertainty Quantification and Reliability

Bayesian frameworks for MRA-based fault diagnosis could provide statistically rigorous uncertainty estimates for diagnostic decisions, enabling more informed and risk-aware maintenance planning strategies. Conformal prediction methods could provide statistically valid confidence intervals for fault diagnosis results, improving the reliability and trustworthiness of automated diagnostic systems.

E. Sustainability and Environmental Considerations

Development of energy-efficient MRA algorithms and hardware for sustainable motor monitoring applications, minimizing environmental impact while maintaining diagnostic performance. Integration of MRA-based diagnostics with circular economy principles for motor lifecycle management and component reuse strategies, supporting sustainable industrial practices.

XII. CONCLUSION

The abovementioned detailed review illustrated the state-of-the-art multiresolution analysis, showcasing how the fusion of advanced signal processing techniques and intelligent machine learning algorithms could benefit rugged induction motor diagnosis. It has a dynamic property and is continually evolving, due to continuous improvement in computational parallelizing capabilities, sensor technologies, and AI methodologies. Moving forward, the successful application of MRA-based motor diagnostics will heavily rely on the progression in addressing various technical challenges, such as optimizing computational complexity reduction, automatic parameter selection, noise tolerance improvement, and system interpretability enhancement. Developing next-generation monitoring through integration with emerging technologies such as IoT infrastructure, edge computing platforms, and quantum processing could provide new capabilities. The significance of dependable condition monitoring will soar as industrial systems get more complicated and interconnected. These increasing challenges and the broadening range of motor-driven system applications can be reliably served with a robust foundation using multiresolution analysis. The significant economic returns on investing in high-end condition monitoring solutions and the ongoing evolution of the underlying technology provide a fertile ground for innovative and intentional application of MRA-based diagnostics. Future studies aim to develop implementable solutions that could be practically implemented in challenging industrial scenarios and further enhance the theoretical knowledge of multiscale signal analysis and pattern recognition.

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