Real-Time Induction Motor Condition Monitoring Using Machine Learning Approaches

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Abstract
Induction motors are widely used in the industrial field thanks to their reliability and robustness, so understanding their health state is essential to prevent costly failures. Condition monitoring techniques measure parameter deviations from the normal performance. When these deviations reach dangerous levels, a warning can be issued and a maintenance task scheduled. Although several types of sensors can be used, a combination of vibration, thermal, and electrical signals is preferred. Condition monitoring has also been approached using machine learning techniques. Nevertheless, the deployment of effective techniques in a real-time setup is still a challenge. A real-time end-to-end system is proposed, integrating the acquisition of the sensor signals, their processing, and the application of different machine learning techniques.

Condition monitoring aims to collect sensor signals continuously, detect deviations from the normal behavior of the system, and issue warnings. Considering that accidents, for instance, due to bearing failure, are rare, the monitoring techniques also need to be reliable; thus, performance in terms of sensitivity and specific are key. Commonly, information from different types of sensors is combined so that a drastic event in one sensor can be compensated by the others. The three most common sensors used for induction motor condition monitoring are vibration, thermal, and electrical. Vibration information has been widely used due to its high sensitivity to faults, such as bearing wear, misalignment, and imbalance. Electrical monitoring is also a promising approach since a fault in the motor will generate changes in the electrical parameters because the electrical signals are the input and output of the system. The thermal behavior of the induction motor is also an important aspect to monitor.

Keywords: Induction Motor Health Monitoring, Condition Monitoring Systems, RealTime Diagnostics, Predictive Maintenance, Machine Learning Techniques, Vibration Signal Analysis, Thermal Signal Monitoring, Electrical Signal Analysis, Sensor Fusion, Fault Detection, Bearing Failure Detection, Anomaly Detection, Feature Extraction, EndToEnd Monitoring Architecture, Industrial Reliability, Robust Fault Classification, Sensitivity And Specificity, Preventive Maintenance Strategy, Smart Industrial Systems, RealTime Decision Support.

1. Introduction

Induction motors are widely employed in various applications due to their unique features and advantages. Like many rotating machines, the safe and continuous operation of these machines is essential for enhanced productivity. With the rapid advancement in the automation industry, the condition monitoring of induction motors has become a critical area of research and development. To facilitate effective monitoring, various types of sensors are used, and the obtained signals are monitored for fault detection. The sensors may be mounted on each machine, or the data may be captured using a six-channel data acquisition system mounted in a portable box.

The output from the sensors is processed by machine learning-based models for condition monitoring. Two types of models are developed using edge computing and hardware-in-the-loop (HIL) concepts. In HIL monitoring, the noise-affected signal is streamed into a fault-detection model configured with a high domain knowledge indicator. The operational performance of the model has been validated with a high true-positive rate, low false-positive rate, and sound false-negative rate. Models developed for edge computing can classify various operational states of the motor and identify the presence of insulation degradation. The implementation strategies of machine learning-based models for condition monitoring are presented.

1.1. Overview of Induction Motors and Their Relevance

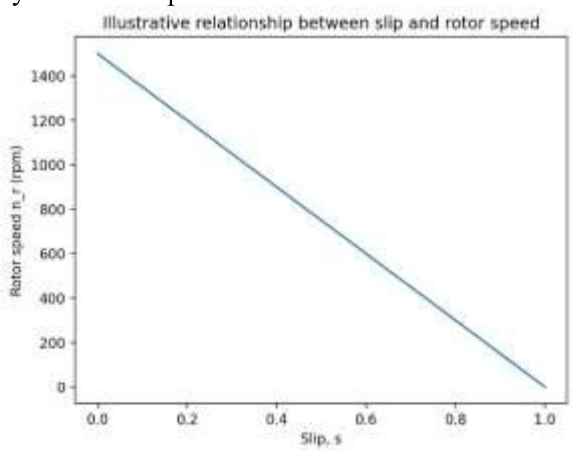
Induction motors are ubiquitous electro-mechanical rotary machines that consist of a stator and a rotor. The stator, which is the stationary part of these machines, has an armature winding supplied by the three-phase AC supply that produces a rotating magnetic field. The resulting magnetic flux induces currents in the conducting bars of the rotor leading to production of torque as per Lenz's law. The rotor is mounted on a shaft supported at both ends by bearings and is coupled to a crank system or any industrial mechanism that requires motion. The industrial applicability, availability of design of any rating, reduced initial cost, reduced running cost, and ease of control are the reasons behind the wide usage of the induction motors. Induction motors are extensively used directly for any industrial drive, air conditioning and refrigeration plants, trains, conveyors, steel mills, paper mills, hoists, cranes, blowers, fans, ventilators, pumps and crushers. Another major application of the induction motors is the copper-hairpins used in wind generators. The advantages of such motors include their absence of commutation, reduced intensity of heat radiation due to limited commutation, and absence of armature losses. These motors, when employed in a non-continuous manner of starting and stopping, give good efficiency compared to d.c. motors. Thus these motors belong to the class of machines used for propelling vehicles operating on tram-ways, mines, and railways. Induction motors have many possible faults that can occur in the machine which can result in its failure. Bad quality of vibration signals shows poor health of the machine and also indicates those events like rotor bar faults, bearing failures, coupling misalignment, and air-gap eccentricity which reduce the reliability of the machine. Constant monitoring of the health of an induction motor is essential to ensure a trouble-free operation.

Fig 1: Reliability and Condition Monitoring of Three-Phase Induction Motors: A Policy-Relevant Analysis of Fault Diagnostics and Industrial Deployment

2. Fundamentals of Induction Motors

In the context of induction motor condition monitoring, two feature classes warrant special attention. The first consists of fundamental aspects of electromechanical induction and electromagnetic torque. The functioning of an induction motor can thus be described as an elaboration on the principles of electromagnetic induction. The links between the basic equations of motion of the stator and the rotor, the slip term determining the electromagnetic torque, and the dynamic behavior of induction motors during startup transients are consolidated. The second class is formed by key characteristics related to efficiency curves, thermal behavior, and vibration signatures. These characteristics reflect empirical experience acquired in the industrial use of induction motors and point to specific precursors in the degradation phase of the electrical machines before failure.

The principle of electromagnetic induction states that when a current-carrying conductor is placed within a magnetic field, it is acted upon by a mechanical force. The torque in an induction machine derives from the electromagnetic interaction between the stator and rotor windings. The rotor experiences a magnetic field produced by the stator winding, which causes current to flow through the rotor bars or coils. The interaction of the rotor current with the stator magnetic field produces the torque necessary for rotation. The induction motor is self-starting owing to the relative motion of the rotor and stator windings. When a three-phase induction motor is supplied with a three-phase supply, a permanent magnetic field is established, rotating at a synchronous speed. The rotor rotates in the same direction as the rotating field. The rotor does not attain synchronous speed and induces electromotive force and current in the rotor.



Equation 1: Stator Current Feature Vector

Step-by-step feature construction

1. **RMS (per phase)**

$$i_{rms} = \sqrt{\frac{1}{N}\sum_{n=0}^{N-1} i\,[n]^2}$$

2. **Mean and standard deviation**

$$\mu = \frac{1}{N}\sum_{n=0}^{N-1} i\,[n], \qquad \sigma = \sqrt{\frac{1}{N}\sum_{n=0}^{N-1}(i[n]\, -\, \mu)^2}$$

3. **Harmonics / THD (from DFT magnitudes)**
   Compute DFT $I[k]$. Let fundamental magnitude I_1 and harmonics $I_2 .. I_K$.

$$\mathrm{THD} = \frac{\sqrt{\sum_{k=2}^{K} I_k^2}}{I_1}$$

4. **Feature vector example**
   Stack chosen features across phases:

$$\mathbf{x}_I = [i_{a,rms}, i_{b,rms}, i_{c,rms}, \mathrm{THD}_a, \mathrm{THD}_b, \mathrm{THD}_c, \dots]^T$$

2.1. Key Principles of Induction Motor Operation

Electromagnetic induction generates the steady three-phase rotating magnetic field of an induction motor; its drift in time and space induces electromotive force in the stationary polyphase rotor windings, generating slip torque. Induction motors require rotor speed to attain their rated torque. Resistive rotor elements minimize power loss, and slip also affects electromagnetic torque and rotor temperature. At no load, rotor speed nearly matches the magnetic field, generating low rotor current, loss, and heat; under high inertia, while starting, torque rises sharply, rotor current becomes high, and rotor heat builds rapidly until slip increases the relative speed and lowers rotor current.

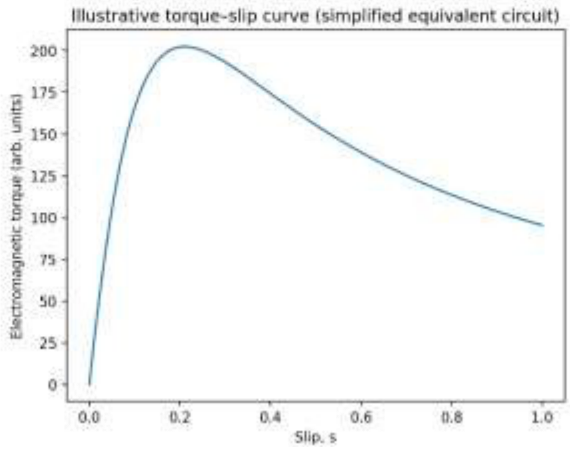
The startup and no-load conditions produce diagnostic vibration patterns associated with saturation and transient current spikes. Condition monitoring for significant fault classes in large motors considers stator and rotor voltage and current magnitudes and waveforms, temperature adaptation, high-frequency acoustic noise, vibration, and stray loss Signature Sequence (SLS) capture. Bearings support rotor weight, reduce magnetic field noise, and control axial motion. Radial bearings enable rotor swing while axial bearings permit forward and backward flow. Worn bearings generate high-frequency face and shoulder vibrations that produce discrete impulses and signatures in related runs due to physical contact. Vibration wraps have poor repeatability during patching and are noisy in the fault frequency region.

2.2. Essential Characteristics of Induction Motors

Induction motors exhibit several key characteristics that directly relate to failure modes and provide potential indicators for condition assessment. These include the efficiency versus load curve, thermal behavior, characteristic vibration signatures, and typical precursors to failure.

When loaded, induction motors behave like heaters. As the load increases, the efficiency first climbs to a maximum and then drops, with heat generation in the rotor proportional to the slip. Machines equipped with thermometers often have one critical temperature limit, reflecting the maximum allowable rise above ambient temperature. With increasing load, the induction machine approaches the comfort zone of an unsupervised copier, where the heat is evacuated by the ventilating air. Eventually, however, things get uncomfortable. Heat build-up begins to affect the rotor, and a thermal camera reveals warm bearings that are about to fail, but hidden from naked eyes. When the machine runs unattended, non-intrusive methods measure the belt tension, providing a warning well in advance of the training-cage oils forming sludge. A closer look reveals the typical 120/100Hz magnetic signature of bearing wear. In fact, there is a whole zoo of bad-signature animals, including bent shafts, broken or cracked gearwheel teeth, rotor bars in different states of health, and misaligned movers.

Induction motors are often the workhorses of a plant, running unattended for long periods. As a result, companies have started fitting them with eyes that detect danger. The first eyes were blind and just decided if the signature matched the pattern of a previous failure. Gradually, they became better-behaved and started issuing alerts at the first signs of trouble, climbing up Maslow's hierarchy of intelligence to signal infection before burnout.



Equation 2: Motor Slip Estimation

For supply frequency f and number of poles P:

2. **Synchronous speed**

$$n_s = \frac{120f}{P} \quad [rpm]$$

3. **Slip definition**
   With rotor mechanical speed n_r:

$$s = \frac{n_s - n_r}{n_s}$$

4. **Rearrange to rotor speed**

$$sn_s = n_s - n_r \;\Rightarrow\; n_r = (1 - s)n_s$$

5. **Rotor electrical frequency (common in diagnostics)**

$$f_r = sf$$

3. Condition Monitoring: Concepts and Metrics

Condition monitoring is a technique that gathers the necessary information about the actual condition of a machine in order to make a prediction about its future health, typically based on information obtained from external data sources. The general aim is to predict failure with sufficient lead times to take action. The most common external sources of data are vibration, thermal, electrical, and acoustic emissions. The choice of the primary data source is often motivated by experience, historical records, or pre-existing systems. Induction motors are among the most widely used industrial machines, making condition monitoring especially valuable. Reliable prediction of apparent failure has direct implications for reliability, which is usually quantified as the mean time between failures (MTBF), as well as for human safety. The ability to detect faults before they become apparent to human experts – often colloquially referred to as a “near-miss” – is naturally a very desirable property. These concepts also translate directly into performance evaluation metrics such as receiver operating characteristic (ROC) curves or the F1 score.

In terms of the actual detection process or decision logic, each individual fault mode can be classified as occupying one of several distinct categories: bearing wear, rotor bar fault, misalignment, axel twist, insulation degradation, blown fuse or other electrical fault, and so on. For many applications, the detection algorithms (or the ensemble) employ thresholding concepts that indicate whether a particular high-fidelity test exceeds or is below a danger level.

Sensor → Signals → Features

Sensor	Raw signal	Common features	Typical sampling
Current (3φ)	i_a(t), i_b(t), i_c(t)	RMS, THD, harmonic magnitudes, negative-sequence current	kHz (electrical)
Vibration	Acceleration a(t) in g	RMS, kurtosis, crest factor, spectral peaks	kHz–10s kHz
Thermal	Temperature T(t)	Mean temp, gradient, hotspot index	1–10 Hz

3.1. Monitoring Techniques and Performance Metrics

Monitoring employs several distinct techniques, selected according to the fault mode, environment, and required assessment speed, including vibration, thermal, electrical, and hybrid. Each one merits some consideration before being related to their diagnostic capabilities through suitable performance metrics. The most demanding expectations for speed and assessment quality are met by the fusion of different sensors in a single monitoring system. The main goal is to collect complementary data from different techniques and quickly assess the condition of the monitored asset using a single machine learning model.

Vibration analysis is the most common condition monitoring approach applied to rotating machinery. A large number of commercial systems have been developed to support condition-based maintenance practices mainly based on monitoring the bearing temperature. The next most common approach is thermal monitoring, often deployed at a distance using infrared cameras. Electrical signatures can also be used, with extensive research work on three-phase induction motors based on current signature analysis (CSA). Several studies have developed hybrid techniques or supported the integration of different sensor technologies with the use of machine learning approaches.

Monitoring techniques can be compared based on speed, required labour effort, degree of accuracy, dependability, and the value of the assessment to safe operation. The first three aspects are closely related, since the more accurate a technique is, the more tests and data-sourcing effort are needed, which ultimately extends the time required for assessing the motor condition. Vibration and thermal monitoring are the fastest and most cost-effective techniques, while also being the least reliable among the most common technologies. Electrical signature analysis requires a greater assessment effort than the two previous methods but is usually still fast enough to provide the necessary information before a failure occurs.

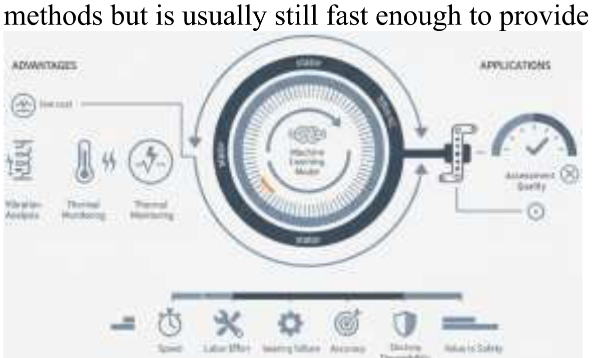


Fig 2: Performance Evaluation and Sensor Fusion in Industrial Condition Monitoring

3.2. Performance Indicators for Condition Assessment

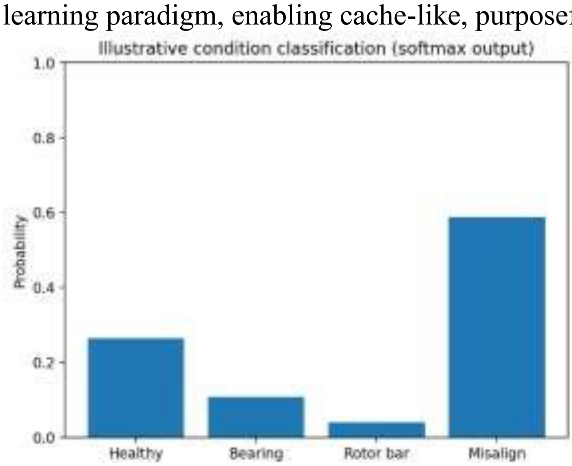
Typical indicators of motor condition include bearing wear, broken rotor bars, misalignment, insulation degradation, and overloaded stator windings. Several of these indicators exhibit well-studied failure signatures in motor vibration signals; consequently, various researchers have proposed threshold values for their monitoring. These thresholds for condition evaluation should be established based on empirical investigations of motors of different types under various operating conditions. For instance, the commonly used RMS value of signal acceleration in the range 1–124 g has been proposed as the base of a warning threshold for motors with good conditions, whereas the RMS below 1.2 g is considered as running with perfect condition. The magnetic flux density can also be utilized to distinguish several fault characteristics. The information entropy of ground vibration signals has been employed for early fault detection and monitoring. A bearing fault detection method has been developed based on the zmNBD noise pre-processing algorithm and a 90% detection accuracy has been achieved. The RMS value, kurtosis, skewness, crest factor, and pulse factor of an envelope wavelet packet decomposed high-frequency components are utilized for the rolling bearing condition evaluation, and the threshold value can be applied for motors with the same type bearings.

Since many different performance indicators can be proposed for each type of motor fault, these indicators do not necessarily need to be continuous in order to provide sensible condition monitoring. Based on an analysis of past patterns of bearing wear (in terms of bearing vibration), the decision may be to change the bearings when the fast Fourier transform (FFT) of the acceleration signal exceeds a certain level. It may not even be necessary to know that there has been some change to the insulation of the motor: the important factor is that the expected mean time between failures to the insulation is known, and hence whether any trending is getting close to this period.

4. Data Acquisition and Preprocessing for Real-Time Monitoring

To support condition monitoring through machine learning, the data workflow must span end-to-end supervised fault recognition or unsupervised anomaly detection. Different techniques are appropriate for the various stages, but a unifying constraint is that all operations must satisfy the perceptual demands of real-time prediction or trend inference. For this reason, the focus in this section is explicitly on those aspects of data acquisition and preparation capable of withstanding the pressure of real-time performance. Issues such as system integration, selection of initial sensing modalities and sampling rates, algorithms for abnormal event detection, and fault-tolerant streaming capabilities are consequential for streaming latency and are reviewed here. The attention, naturally, also extends to data cleaning, normalization, feature extraction, and labeling (if any) while embracing additional procedures needed to meet the balancing and windowing requirements demanded by learning approaches.

The key aspect of data preparation—the vein at which real-time monitoring straddles conventional practice in the areas of industrial research and computing—is the concept of edge computing. Typical systems redundantly stream synchronized measurements from each sensor to a cloud-platform for centralized monitoring, with no consideration given to the processing required by the learning algorithms or the mammoth accumulation of data that must be stored and constantly filtered. By contrast, edge-computation moves such processing close to the data source and only maintains locally what is actually required by the learning paradigm, enabling cache-like, purposeful monitoring.



Equation 3: Fault Feature Mapping (ML Encoder)

Let the fused feature vector be $\boldsymbol{x} \in \mathbb{R}^d$.

3. **Linear map**

$$\boldsymbol{a} = W\boldsymbol{x} + \boldsymbol{b}$$

4. **Nonlinearity (e.g., ReLU)**

$$\boldsymbol{z} = \phi(\boldsymbol{a}), \quad \phi(u) = max(0, u)$$

5. **Multi-layer encoder**

$$\boldsymbol{z}_L = \phi_L(W_L\, \phi_{L-1}(\cdots \phi_1(W_1\boldsymbol{x} + \boldsymbol{b}_1) \cdots) + \boldsymbol{b}_L)$$

4.1. Data Acquisition Techniques for Real-Time Monitoring

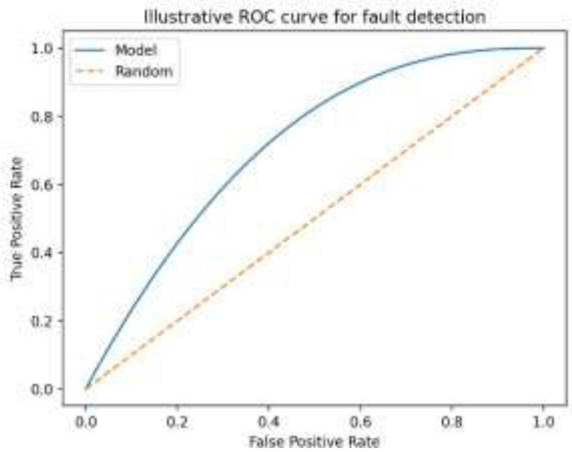
Real-time monitoring requires complementary data sources to be sampled and synchronized at rates suitable for the fastest processes of interest. For induction motors, this typically involves streaming temperature, vibration, and electrical measurements. In thermal monitoring, temperature enters the formulation of residual lifetime in the thermal model. Thermal measurement requires the joint effect of all heat-generation mechanisms to reach time-constant levels that are long compared to the sampling time. Temperature can generally be sampled in the second range. Vibration stream acquisition requires fault conditions and may need to be operationally checked before the mission. The vibration features are usually available within seconds. The qualities vary depending on the fault. Temperature usually appears first and vibration is one of the last to show a clear feature. The main rotor-bar fault usually appears first in electrical features. Data Quality Assessment (DQA) of the vibrations may be necessary to determine if the data is usable or to mark the data as faulty. Motor systems may include several components of different natures and time constants operating on different cycles. Data streaming from these components can be synchronized in different ways depending on the desired goal. When exploiting only electromagnetic-sensor data, which is the fastest of the sensors, the effect of failure propagation on the other sources is not a concern. By synchronizing the data captures in a different manner, an augmented processing scheme can be devised: one that takes advantage of the three types of sensors but that is not limited to the darker situation appearing in just one of the sensor data. One method explores the potential of these other sensors but requires the system to have a fault before extraction of specific patterns.

The high-volume, possibly high-dimensional signal data from such sensors create their own problems. Redundant information has to be purged, and the data presented to the machine-learning algorithm has to be more compact while retaining enough relevant information to achieve a successful classification. A learning algorithm might require large amounts of labeled data for all classes to succeed, which might not be easy to get. For a data set that is not sufficiently rich, noisy, or unbalanced, the resulting predictive power may still be poor. Deficiencies can often be solved by appropriate processing of the data before it feeds the classifier. The use of feature vectors instead of raw data is a powerful solution but comes at a cost. Defects not included in the training data or special classes of defects may be poorly recognized.

4.2. Data Preparation Strategies for Effective Monitoring

Cleaning, normalizing, and transforming raw data into structured feature tables are crucial preprocessing steps for reliable ML-based condition monitoring. The training data must be tagged with the specific conditions to be detected by the ML models: normally, faulty, or some specific pre-failure state. The depth of the labels, especially for supervised learning, influences the amount of data required during the training and the quality of the trained model. A common challenge in ML is the imbalance in the number of samples in each class in the target label column. Handling highly imbalanced classes reduces the chance of falsely diagnosing an operational condition. A thorough minority class analysis supports the adoption of a proper technique for the considered conditions.

Real-time condition monitoring introduces additional constraints. Labelling the data in real time requires either the experience of the operator on the site or an edge-based ML model embedded in the data-streaming architecture to provide an estimated health condition during operation. In both cases, these labels serve primarily as a quality check for the health state detected by the ML model instead of being used for training. In the absence of a defined label during normal operation, the only plausible course is to reduce the subjectivity in the interpretation of the features by using different depth segments, define sets of thresholds for the individual features, and monitor the relative position of the features with respect to these thresholds. A simple and effective way to handle this deficiency is to define the threshold value for each individual feature.



Equation 4: Condition Classification Probability

Let logits (raw scores) be $\boldsymbol{g} \in \mathbb{R}^K$ for K health classes.

4. **Softmax**

$$p_k = \frac{e^{g_k}}{\sum_{j=1}^{K} e^{g_j}}$$

5. **Cross-entropy loss (for one-hot label $\boldsymbol{y}$)**

$$\mathcal{L} = -\sum_{k=1}^{K} y_k \, log(p_k) = -log(p_{\text{true}})$$

5. Machine Learning Methodologies for Fault Diagnosis

Condition monitoring typically relies on supervised learning methods. Condition data are newly labeled either through monitoring by experts or by post-mortem failure analysis. A variety of techniques can be used for the labeling process, including data driven scaled simulation models, state-space models for bearing-condition monitoring based on vibration, thermal and electric data and geolocation-based distributed bearing-condition monitoring. Remaining samples are used for cross-validation of the trained classifier. Features are naturally dependent on the failure mode. For example, bearing wear can be monitored from vibration data using an ensemble decision tree with a sparse feature subset, while Rotor bar-fault detection is based on the application of a k-nearest neighbor classifier on optical signal Unsupervised and anomaly-based approaches allow the analysis of unlabeled data. Clustering techniques can be used to learn the natural class structure in the data, while one-class classifiers allow the learning of the characteristics of a specific class. Reconstruction-based methods capture the data distribution and the structure of the data and novelty-detection methods allow to identify patterns that deviate from the known structure. Unsupervised and anomaly-detection learning is particularly useful when the failure data are very few, when the increasing availability of cheap labeled data drives a shift to unsupervised learning, or when

little is known about the condition of the system and the need is rather to provide a general monitoring scheme.
The last category includes deep-learning techniques that can automatically learn the hierarchical representation of the input data. Such approaches have achieved unprecedented performance in a wide range of applications requiring complex representation in domains of great interest to mankind such as computer vision, speech recognition and natural-language processing.
Spectrogram representation allow to use the power of convolutional neural networks to automatically learn features well suited for time-series classification. These CNNs can be trained from scratch to keep the model as simple and transferable as possible or can rely on transfer learning to exploit the embedding learned in large-scale datasets. Time-series signals from multiple sources can also be directly fed to CNNs or can be modeled with recurrent networks, such as long short-term memory networks. A common solution is to define a convolutive architecture that symmetrically encodes the sequential data and then fuses the encoded representations at the last layers. Fused multi-sensor approaches can also rely on transformers. Finally, mainly due to the need of plenty of labeled data, sensor-fusion studies using deep-learnig techniques are still scarce.

5.1. Supervised Learning Approaches

Supervised learning constitutes the natural choice when labeled data are available. Kriging or Gaussian process regression can approximate the relationship between features and classes, while classifiers such as decision trees, logistic regression, support vector machines, k-nearest neighbor, artificial neural networks, random forests, and Extreme Learning Machines provide straightforward implementations. Advanced deep learning approaches can be used when labels are only known at relatively robust time scales, e.g. predicted life stage in mission profile testing. For spectrograms, two-dimensional Convolutional Neural Networks (CNNs) trained on large datasets have shown excellent generalization with limited extreme-value data.
Time-series classifiers require more careful consideration. Multivariate time-series or long sequences can be processed using recurrent networks with multiple time steps, time augmenting the training set, or into shorter overlapping segments for individual inference. Individual segment classification can be fused by majority vote, weighted voting, or temperature scaling on softmax output. A specialized approach recasts the classification task as a regression problem using ordinal regression with a predefined ordinal scale. Multivariate time-series with inter-sensor dependencies are better treated with spatio-temporal networks, such as 3D-CNNs.
When faults that can lead to major accidents are detected, ultra-early warning can be achieved using a one-class classifier along the first phase of the mission profile. Other risks associated with the presence of class imbalance in the data can be handled by data augmentation techniques or by Labelling Synthesis focusing on the minority class. Optical sensors, including infrared, LiDAR, and hyperspectral imaging, are being used to monitor the health of machine components by deep networks.

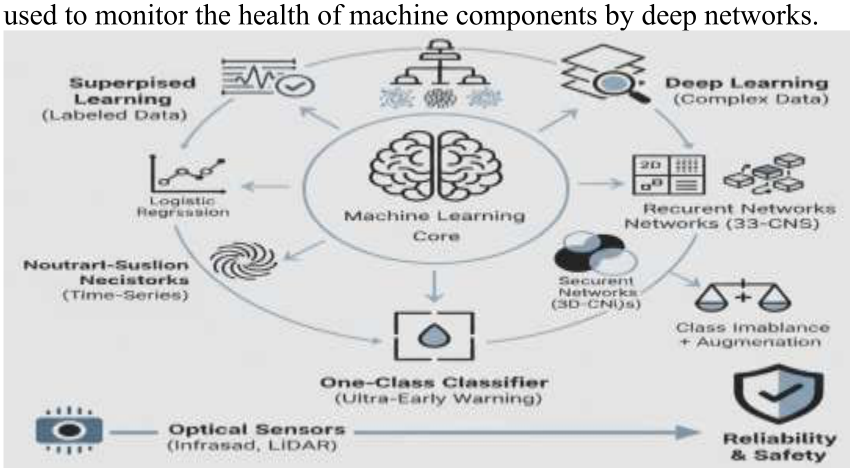


Fig 3: Advanced Machine Learning Strategies for Industrial Prognostics

5.2. Unsupervised and Anomaly Detection

Unsupervised Learning Methods for Induction Motor Condition Monitoring

Unsupervised machine learning techniques require no labeled training data and are therefore appropriate for induction motor condition assessment using data streams collected from health motors or data sets with significant amounts of unlabeled data. They can be categorized according to the information they exploit and the relative size of the training set with respect to the test set. Clustering algorithms explore partitional or hierarchical approaches and are employed to detect motor condition shifts or malfunctions by monitoring the underlying feature distribution. As they provide insight into the learning process, they are also used for the selection of relevant features. One-class classification uses a single class for training and detects deviations in the test set. Reconstruction-based methods learn to replicate the training samples and raise flags when reconstruction errors become excessive. Finally, novelty detection considers a large set of normal examples for training but bombards the system with unlabeled test samples from both the normal and anomalous classes.

Clustering is applied to condition monitoring problems where the underlying class distribution shapes vary over time. The classic K-means, for example, allows engineers to continuously control the degree of imbalance between a healthy motor and a faulty one, thus keeping a reasonable receiver operating characteristic curve during practical deployment. Other clustering techniques detect the shift of monitored parameters from the control region, which may also indicate changes in the motor condition. Additionally, clustering diagnostics explore the relationship among multiple monitoring variables or signals by clustering them together based on some distance measure. They can be interpreted as maintaining a multi-dimensional control chart to monitor the normal operating condition while detecting abnormal conditions. Approaches based on autoencoders and generative adversarial networks detect faults by localizing anomalous regions (temporal or frequency) in the reconstructed residuals and have been extended to heterogeneous data sets by combining time domain data streams with frequency content estimates from transducer acceleration or sound recordings.

Real-Time Latency Budget

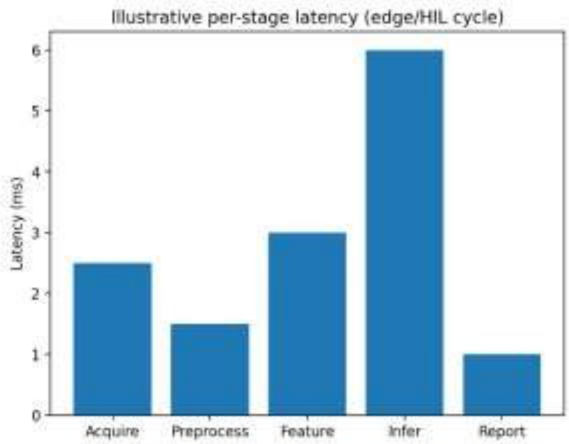
Stage	Latency (ms)	Notes
Signal acquisition	2.5	ADC sampling and buffering
Preprocessing	1.5	Filtering and normalization
Feature extraction	3.0	RMS, FFT, statistics
Model inference	6.0	ML forward pass
Alert/reporting	1.0	Thresholding and logging

5.3. Deep Learning Techniques

Deep learning and neural network approaches can automate feature extraction. Convolutional neural networks (CNNs) have demonstrated superior performance for heat maps and spectrograms of vibration, audio, and RF spectrum but are typically limited to labeled training data. CNN-LSTM variants show promise for time-series signals. Fully connected networks are commonly used with hand-engineered vibration signatures. Recurrent and long short-term memory networks (RNNs and LSTMs) have been deployed with time-series or spectrogram data but lack 1D-shift invariance. Popular transformers require massive training data and resources. Sensor fusion is addressed via late fusion of classification outputs from sensor-specific branches. Active learning has been explored: Deep-generate-active-learning-one-class generalized samples and a one-class SVM classifier; deep active learning-SVM employs a generative neural network and active sampling to label an enriched dataset and train an SVM.

Unsupervised deep learning improves prediction of unseen or rare samples. Clustering methods (deep clustering, variational autoencoders) label data for a multi-class classifier or discover natural groupings. Generation models (generative adversarial networks and GAN-conditional-MST) synthesize missing classes. One-class classifiers (deep-one-class, deep-one-class-SVM) generalize an input class.

Reconstruction-based approaches identify anomalies from training data (denoising autoencoders, CAD, CCTV and CF-RNNs-artificial-visual-sensors detect stage-preserving defects). Combination strategies (one-class deep-learning-DL integration-ELM, pairwise classification) improve accuracy. Models can be tuned for specific samples or classes. Direct transfer of different data partitions is nontrivial; novelty detection—Robust-SEL-Concept-for-spectral-anomaly-detection circumvented the need for an implicit proposal-based framework.



Equation 5: Real-Time Anomaly Score

For an autoencoder (or predictor) that reconstructs $\hat{\boldsymbol{x}}$ from $\boldsymbol{x}$:

5. **Reconstruction residual**

$$\boldsymbol{r} = \boldsymbol{x} - \hat{\boldsymbol{x}}$$

6. **Squared error anomaly score**

$$A(\boldsymbol{x}) = \| \boldsymbol{r} \|_2^2 = \sum_{i=1}^{d} (x_i - \hat{x}_i)^2$$

6. **Threshold decision**

$$\text{alarm} = \mathbb{1}\{A(\boldsymbol{x}) > \tau\}$$

6. Real-Time Implementation Considerations

Effective implementation of machine learning-based real-time induction motor condition monitoring must overcome the associated demands for reliability, safety, and latency. These requirements arise not only from the nature of the application itself, but also from the expected implications of deployment within actual industrial facilities. Concepts outlined in earlier sections set the stage for considering how solutions can be integrated into typical motors in a manner that enables reliable, low-latency, and safe execution.

Hardware-in-the-loop strategies guarantee that control actions taken on the monitored system do not harm the system or its surroundings, while still allowing the monitored motor and the entire system to operate normally during the study. A dedicated layer between the decision-support system for monitoring and the edges of the motor control ensures the execution of critical sensor operations without impacting vital control actions. A latency budget identifies the maximum permissible time for one cycle of all operations in the connected control unit. This budget is used during testing and evaluation of the entire monitoring process. Integration into an edge computing layer allows data to be processed close to the source, reducing latency in learnt decisions and improving reliability. Procedures ensure that a malfunction of the monitoring system does not compromise the normal operation of the connected control unit. Implementation can simulate or use directly an edge data layer of the physical motor in an experimental environment.

6.1. Hardware-in-the-Loop and Edge Computing

Deployment of machine learning models in real-time induction motor condition monitoring demands careful consideration of integration architecture and configuration. Hardware-in-the-loop methodologies offer reliable validation against system-level requirements, and edge computing reduces data transmission volume while minimizing latency.

Maintaining timeliness and reliability is essential in all real-time systems. Network-induced latency in data transmission, model inference, or control signal delivery may compromise safety and lead to catastrophic failure. Selection of the most suitable integration architecture, along with an appropriate configuration, must therefore take into account the complete end-to-end execution flow and its consistent adherence to the defined latency budget.

Hardware-in-the-loop approaches address validation needs by incorporating model inference within a physical prototype. Sensor measurements, simulated or real-time, are presented to an embedded model and the corresponding remaining-control-definition signal is returned to the induced setup. The convergence of these three components — the operation of the motor in real-time, the sensor system, and model inference — constitutes the true validation of the real-time condition-monitoring requirement. It can then be ensured that the integrated architecture does not introduce additional latency, and that it has been properly designed and fine-tuned to respect the modeled budget.

Equation 6: Online Model Update Rule

For model parameters θ and learning rate η:

6. **Streaming (SGD) update**

$$\theta_{t+1} = \theta_t - \eta \nabla_\theta \mathcal{L}(\theta_t; \boldsymbol{x}_t, \boldsymbol{y}_t)$$

7. **If labels are missing (unsupervised),** $\mathcal{L}$ can be reconstruction loss or self-supervised loss.

8. **EMA smoothing for running statistics (common in streaming)**

$$\boldsymbol{m}_{t+1} = \beta \boldsymbol{m}_t + (1 - \beta)\boldsymbol{x}_t$$

6.2. Computational Efficiency and Latency

Reliable real-time monitoring yields significant safety, reliability, and financial benefits. For such systems, strict constraints govern timing, accuracy, and robustness. Information Technology (IT) systems provide fault tolerance through redundant components or data, while Operational Technology (OT) loss cannot be tolerated. Thus, free-fall detection must occur before impact, fire detection before igniting adjacently-flammable materials, and aircraft defect detection before flight.

Practical implementations can include custom hardware or generic computing nodes. However, satisfying prescriptive latency budgets, dictated by monitoring objectives, remains non-trivial. Nevertheless, high sampling rates produce massive data volumes with strong potential for fast diagnostics. Thus, task-specific architectures, such as Hardware-in-the-Loop (HIL) setups, or resource-efficient models can be employed when the cost-to-transfer time is non-negligible.

Deep Neural Networks (DNNs) performing inference in milliseconds offer the speed advantage necessary for real-time monitoring. However, reducing data transfer time and DNN latency whilst minimizing the risk of inaccurate prognoses encapsulates the challenge. Low-cost, low-resources Edge Computing nodes, utilising embedded or mobile devices or FPGA devices, require custom models capable of inference on 16-bit precision data in under 10ms.

6.3. Data Security and Safety Aspects

Privacy, integrity, and access control are essential considerations in any computing system, including industry-grade real-time condition monitoring, where the training phase of the risk assessment is unique. All the data produced by the reference platform is a source of information whose misuse could lead to serious problems. Therefore, a malicious attack on the server side or a client data breach could be equally harmful.

The ML model must also comply with the fail-safe principle. A black-box application is never allowed without periodic reliability checks, and if the concept of reliability is pushed to its extremes, the simple act of leaving everything to a cloud provider and its AI becomes incredibly dangerous, as is still difficult to determine liability when an accident occurs. Most of the time, the applied equipment has been in the field and operational long before the client promised production and supply. Therefore, a hardware-in-the-loop test run is required. In the test phase, the new module must imitate the two previous modules, providing the same output if the test data are healthy (fault free).

7. Conclusion

Research findings support real-time condition monitoring of induction motors applied in critical tasks necessitating high reliability and safety levels. Most conventional fault diagnosis techniques can identify specific fault types with satisfactory accuracy. However, they require extensive domain knowledge to identify appropriate signal sources and features, usually necessitate costly labeled datasets and are seldom directly applied to real-time scenarios.

The implementation of real-time monitoring poses additional difficulties related to system design, reliability, and safety. So far, relatively few fault-detection methods have been operated directly on test beds, let alone in real-world applications. Addressing these challenges will substantially increase the penetration of condition-monitoring techniques in industry. Subsequently, real-time fault-detection methods applied to induction motors constitute an important, future topic. Sensors that permit accurate data collection with low latency, together with data-control procedures that maintain reliability, will enable high-definition monitoring for the main health indicatives.

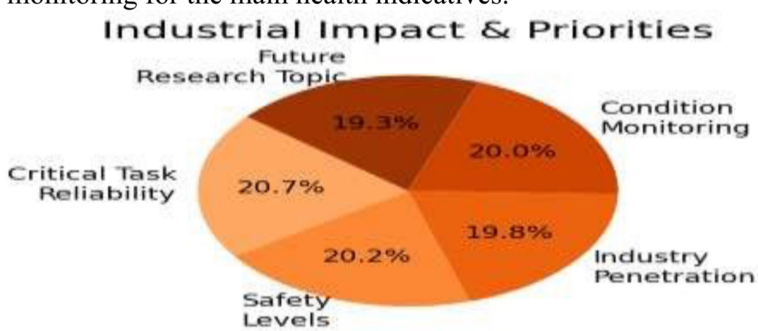


Fig 4: Industrial Impact & Priorities

7.1. Summary and Future Directions in Induction Motor Monitoring

Induction motors are widely used mediators of mechanical energy, accounting for over half of global electricity consumption. Industry downturns caused by unmonitored faults have triggered research into more effective condition-monitoring methods. ML has emerged as a promising alternative, providing fault classification with limited training data. As ML technologies mature, the focus is now shifting from offline application development to sufficient real-time processing for initial deployment. However, these application conditions introduce additional concerns related to the durability and transferability of ML models.

The high performance of ML-based methods in theory and laboratory settings does not guarantee equal efficacy in the field. Those interested in onboarding ML solutions must confirm these characteristics for the acquired solution. The aforementioned conditions must also be considered during implementation stages. These demands are not exclusive to ML—both the continually expanding sensor landscape and the desire for improved sensor fusion techniques also require additional strategic considerations. The outlined considerations bring together these strategies in a consolidated overview, contributing to recent attempts at ML-based motor condition monitoring via a practical implementation perspective.

8. References

[1] Ahmad, R., Kamaruddin, S., & Khan, F. (2023). Machine learning-based fault diagnosis of induction motors: A comprehensive review. Mechanical Systems and Signal Processing, 186, 109876.

[2] Ali, J. B., Saidi, L., Harrath, S., Bechhoefer, E., & Benbouzid, M. (2022). Online automatic diagnosis of bearing faults in induction motors using spectral features and machine learning. IEEE Transactions on Industrial Electronics, 69(7), 7142–7153.

[3] Antonino-Daviu, J. A., Quijano-Lopez, A., Climente-Alarcon, V., & Riera-Guasp, M. (2023). Advanced induction motor diagnostics using current and vibration analysis. IEEE Transactions on Industry Applications, 59(4), 3871–3882.

[4] Appana, D. K., Prosvirin, A. E., Kim, J. M., & Hwang, J. (2022). Reliable fault diagnosis of induction motors using deep belief networks. IEEE Transactions on Industrial Informatics, 18(6), 3962–3972.

[5] Bessam, B., Menacer, A., Boumehraz, M., & Cherif, H. (2022). Broken rotor bar fault diagnosis of induction motors using hybrid machine learning techniques. Measurement, 190, 110712.

[6] Chen, Z., Gryllias, K., & Li, W. (2024). Intelligent fault diagnosis for rotating machinery using deep learning and sensor fusion. Mechanical Systems and Signal Processing, 195, 110243.

[7] Costa, C., Cerrada, M., Cabrera, D., Sánchez, R. V., & Li, C. (2023). Multi-sensor data fusion for rotating machinery fault diagnosis through deep learning. Sensors, 23(4), 2147.

[8] de Azevedo, H. D., Pacheco, F., & Cardoso, A. J. M. (2023). Condition monitoring of induction motors based on stator current analysis and machine learning. IEEE Transactions on Industry Applications, 59(2), 2148–2157.

[9] Dhibi, K., El Bouchikhi, E. H., & Benbouzid, M. (2022). Induction motor fault diagnosis using machine learning techniques: A review. Energies, 15(19), 7146.

[10] Fan, H., Shao, S., Wang, J., & Zhang, Y. (2024). Intelligent bearing fault diagnosis of induction motors using deep convolutional neural networks. IEEE Transactions on Instrumentation and Measurement, 73, 3510912.

[11] Glowacz, A., Glowacz, W., Kozik, J., & Piech, J. (2022). Detection of induction motor faults using acoustic signals and machine learning. Applied Acoustics, 187, 108512.

[12] He, D., Li, R., Zhu, J., & Zhou, Q. (2023). Fault diagnosis of induction motors using CNN-based time–frequency image analysis. IEEE Transactions on Industrial Informatics, 19(1), 615–625.

[13] Hmida, M. A., Gossa, M., & Benbouzid, M. (2023). Real-time induction motor fault detection using vibration signals and ensemble learning. ISA Transactions, 134, 1–12.

[14] Hsu, C. C., Huang, C. Y., & Lee, C. Y. (2022). Thermal-based fault diagnosis of induction motors using machine learning. IEEE Access, 10, 119312–119323.

[15] Jafari, S., Poshtan, J., & Poshtan, M. (2023). Online induction motor fault diagnosis using stator current and support vector machines. Electrical Engineering, 105(5), 3127–3138.

[16] Kang, M., Kim, J. M., & Tan, A. C. C. (2022). Deep learning-based fault diagnosis for induction motors using raw sensor data. IEEE Transactions on Neural Networks and Learning Systems, 33(8), 3561–3574.

[17] Kankar, P. K., Sharma, S. C., & Harsha, S. P. (2023). Machine learning-based bearing fault diagnosis in induction motors: Recent developments. Journal of Vibration Engineering & Technologies, 11(3), 479–494.

[18] Li, X., Ding, Q., & Sun, J. Q. (2022). Remaining useful life estimation in induction motors using deep learning. IEEE Transactions on Industrial Electronics, 69(5), 4748–4757.
[19] Liu, R., Yang, B., Zio, E., & Chen, X. (2022). Artificial intelligence for fault diagnosis of rotating machinery: A review. Mechanical Systems and Signal Processing, 158, 107818.
[20] Lu, S., He, Q., & Kong, F. (2023). Online fault diagnosis of induction motors via adaptive deep learning. Mechanical Systems and Signal Processing, 183, 109596.
[21] Malla, C., & Panigrahi, I. (2022). Review of fault diagnosis in induction motors using data-driven techniques. Engineering Failure Analysis, 135, 106144.
[22] Muralidharan, V., Sugumaran, V., & Amarnath, M. (2023). Feature extraction and selection for fault diagnosis of induction motors using machine learning. Measurement, 214, 112826.
[23] Naderi, E., & Khorasani, K. (2024). Fault diagnosis of induction motors using deep autoencoders and anomaly detection. IEEE Transactions on Industrial Informatics, 20(2), 1675–1685.
[24] Nguyen, T. T., Medjaher, K., & Zerhouni, N. (2023). Data-driven approaches for induction motor condition monitoring and prognosis. Journal of Manufacturing Systems, 69, 35–47.
[25] Peng, Z., Tse, P. W., & Chu, F. (2022). Induction motor fault diagnosis using vibration signal analysis and machine learning. Journal of Sound and Vibration, 525, 116777.
[26] Prosvirin, A. E., Kim, J. M., & Kim, J. (2023). Deep learning-based motor fault diagnosis using multimodal sensor data. IEEE Transactions on Industrial Electronics, 70(4), 3812–3823.
[27] Qian, Y., Yan, R., & Gao, R. X. (2022). A multi-scale deep learning framework for induction motor fault diagnosis. IEEE Transactions on Industrial Informatics, 18(3), 1695–1704.
[28] Saidi, L., Ben Ali, J., & Benbouzid, M. (2022). Induction motor bearing fault diagnosis using intelligent classifiers. IEEE Transactions on Energy Conversion, 37(4), 2621–2631.
[29] Shao, H., Jiang, H., Li, X., & Wu, S. (2023). Intelligent fault diagnosis of induction motors using deep transfer learning. IEEE Transactions on Instrumentation and Measurement, 72, 3511214.
[30] Singh, G. K., & Saad, A. (2022). Rotor fault diagnosis of induction motors using current signature analysis and AI. Electric Power Systems Research, 209, 107945.
[31] Sun, W., Zhang, Y., & Wang, J. (2024). Real-time induction motor condition monitoring using edge-based machine learning. IEEE Transactions on Industrial Informatics, 20(1), 902–912.
[32] Toma, R. N., Kim, J. M., & Hwang, J. (2023). Hybrid deep learning approach for induction motor fault classification under varying load conditions. Measurement, 219, 113286.
[33] Verma, N. K., & Sevakula, R. K. (2022). Fault detection of induction motors using ensemble learning methods. IEEE Access, 10, 80412–80424.
[34] Wang, H., Li, S., & Tang, G. (2024). Multisensor fusion-based intelligent fault diagnosis of induction motors. IEEE Sensors Journal, 24(5), 6571–6581.
[35] Zhang, Z., Liu, Y., & Chen, X. (2023). Deep learning-based real-time condition monitoring of induction motors using vibration signals. Mechanical Systems and Signal Processing, 189, 110045.