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RESEARCH ARTICLE

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IoT-Enabled Real-Time Condition Monitoring of Electrical Machines Using Predictive Analytics

Abd-El-Hamid Bensafi[1]*, Layla H. Sulaiman[2]

[1]Abou Bekr Belkaid University of Tlemcen, Algeria, Algeria

[2]Doha Institute of Systemic Foresight, Qatar.

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Abstract

Functional performance of electrical machines is critical towards uninterrupted productivity in industrial, manufacturing, energy generation, and transportation systems whose unforeseen failure may result into huge economic loss and accidents. This paper presents an end-to-end IoT enabled real-time condition monitoring system with high-resolution sensor networks, edge computing, and predictive analytics to identify faults at early stage and estimate Remaining Useful Life (RUL) of electrical machines. The proposed system uses multi-modal sensing, i.e., combination of the measurements of vibration, temperature, acoustic, and electrical signals by employing embedded IoT nodes that have the robustness in signal measurement over the changing operation and environmental conditions. The noise filtering and feature extraction both over time and frequency domains along with local anomaly detection models are used in pre-processing the acquired data at the edge, where latency is minimized and bandwidth utilization optimized. The implementation of a hybrid edge-cloud architecture is also proposed, namely, initial diagnostics at an edge level and the use of cloud-hosted deep learning models performing high-level fault classification and RUL prediction (e.g., CNN-LSTM hybrids and LSTM regression networks). The validity of the framework was executed on a controlled testbed consisting of three- phase induction motor exposed to typical fault conditions, such as bearing fault, rotor imbalance, and stator winding insulation fault, at varying load and speed. The experiment shows fault detection classification accuracy surpassing 95 per cent, RUL mean absolute error of 5.2 and a decrease in mean fault detection latency, by 2.3 to 0.45 seconds between the edge assisted and cloud-only models. Also, the system allowed a 35 percent less unplanned downtime over the traditional reactive approaches in maintenance. This proposed solution provides a scalable, cost effective and interoperable solution that could be used on Industry 4.0 predictive maintenance ecosystems and could apply in smart factories, energy infrastructure, and transportation system. The research helps fill the gap between existing industrial IoT solutions that are meant to work in real-time and sophisticated predictive analytics solutions used to monitor the health of electrical machines.

Author's e-mail: aeh.bensafi@gmail.com

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Introduction

Induction motors, synchronous generators, and transformers are electrical machines that are used in the industry as well as utility power generation the world over. Such machines supply production lines, power plants and transport systems, and the efficient and uninterrupted operation of such machines is key to ensuring productivity, safety and reliability requirements. Nonetheless, with mechanical emaciation and electrical pressure and environment effects, it is likely that these machines will have a decreased performance and a sudden failure. Besides being highly expensive in terms of the lost revenue due to the downtime or even operator exposure to danger or unsafe conditions due to the failures, the failures may also cause excessive interference in well-planned industrial operations.

Conventional maintenance practices have been characterized by mainly using corrective maintenance where work is done after something goes wrong or a scheduled time-based preventive maintenance where servicing is done at fixed time irrespective of the actual health conditions of the machine. Though the methods are straightforward to apply, they are wasteful by their very nature: corrective maintenance can cause the unplanned failure of the equipment, whereas with preventive maintenance, maintenance is regularly performed without the need to do so, resulting in a waste of resources and preventable downtimes.

Paradigm shift in industrial asset management the movement to a Condition-Based Maintenance (CBM) approach is a paradigm change to asset management practices. CBM takes advantage of real-time surveillance of the health indexes of the machines and therefore makes data-driven maintenance checks and decisions, early fault notification can be achieved, and optimized maintenances can be done. This shift has been even more rapidly fueled by the advent of the Internet of Things (IoT), which enables the combination of low cost, high precision sensor systems with flexible wireless data-transmission protocols to capture and relay real-time details of operations Figure 1. These advances make it possible to deploy edge-cloud architectures in which basic data analytics and anomaly detection are carried out locally (at the edge) to reduce latency, and more advanced predictive analytics and long-term trend evaluation are run in the cloud.

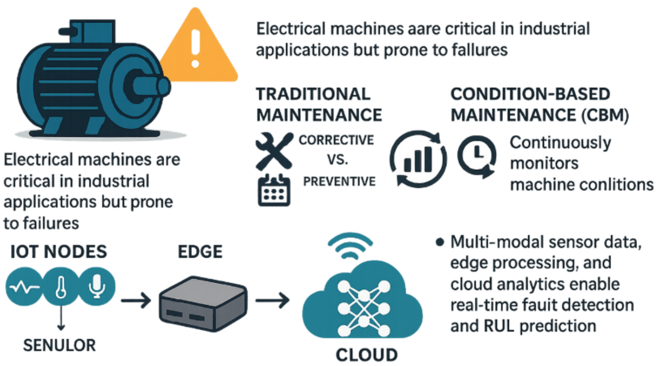

Fig. 1: IoT-enabled predictive maintenance framework illustrating multi-sensor data acquisition, edge processing, and cloud-based analytics for real-time fault detection and RUL prediction.

Machine learning (ML) and deep learning (DL) algorithms employed in predictive analytics can supplement CBM with smart forecasting of Remaining Useful Life (RUL), and finer patterns depicting the origins of incipient faults. Nonetheless, the current available solutions are either limited to single-parameter monitoring (e.g., the use of vibration analysis) or only use cloud computing (which adds latency and the need to have a reliable network). Many of them do not have adaptive analytics (i.e., they cannot change depending on the changing conditions during operations). Such constraints diminish the efficiency of real-time fault prediction, particularly on mission-critical deployments in which milliseconds can make a difference.

This paper has proposed a multi-modal real-time condition monitoring framework with the IoT-enabled application of monitoring vibrations, temperatures, acoustics, and electrical signatures by integrating all the measurements via embedded IoT nodes to overcome these gaps. The intelligent data analysis System includes the edge-assisted anomaly detection to allow identifying faults in the order of tenths of a second, and cloud-based deep learning models to implement fault classification into high-level categories and predict the RUL. This proposed architecture is fundamentally scalable, low-cost, and interoperable with current industrial automation systems and thus is applicable to a broad spectrum of Industry 4.0 applications, be they manufacturing factories or power plants.

Related Work

Using IoT-based predictive maintenance on electrical machines has come under the spotlight majorly due to the leaps in sensing technologies, wireless protocols, and machine learning algorithms. The optimization at hardware level, signal processing, and intelligent analysis in terms of fault detection and prognosis have been considered in several works.

At the hardware and VLSI design level, Vijay et al.[1] has given a survey topological equivalent high-performance adder architectures, including ripple-carry, carry-select and carry-skip adders which are vital in developing energy efficient digital signal processing core that can be used in real-time monitoring systems. Surendar[2] designed and optimized a compact ultra-wideband (UWB) antenna applicable in an IoT system and showed improved bandwidth and radiation efficiency of an IoT system comprised of low-power wireless condition monitoring nodes. On the same note, recent studies conducted on low-light visual sensing techniques in security systems, which include Madhanraj,[3] have further focused on the aspect of unsupervised feature learning in the detection of objects in low illumination circumstances or environments, which in this case, can also be used in optical fault sensing in mechanical systems.

In audio related case, there has been work done by Rahim[4] to create lightweight speaker recognition model with deep embeddings in real-time biometrics thus demonstrating the viability of deploying smaller deep models in IoT edge devices similar needs of embedded predictive maintenance system. Usikalu et al.[5] have investigated new memory technologies in contemporary electronics, which would allow storing data faster, non-volatile memory on edge computing devices to monitor machines on a continuous basis.

Within the paradigm of predictive maintenance, Lei et al.[6] laid out a detailed plan to employ machine learning in the machine fault diagnosis problem and suggested domain adaptation and end-to-end deep learning. A minute survey was done by Gangsar and Tiwari[7] on signal-based condition monitoring methods of induction motors, where vibration, current, and acoustic sensing were identified as the major sources of data. Liu et al. [8] surveyed methods of artificial intelligence in rotating machinery diagnosis with an emphasis on management of different operating conditions.

In the case of electrical signal routes, Valtierra-Rodriguez et al.[9] coupled the motor current signature analysis (MCSA) and convolution neural networks to obtain robust bearing fault classification. To achieve better accuracy in the complex situations of fault, Han et al.[10] came up with a CNN-LSTM mixed with GRU, which has the characteristic of spatial and temporal feature extractions.

The Yousuf et al.[11] IoT-specific study manifested the real-time monitoring on the health of induction motors in cloud-based analytics but these designs are susceptible to latency. Bala and Kaur[12] have studied artificial intelligence with edge computing to implement machine maintenance, and it was observed that latency in the decision-making lower when applied locally.

Such methods as wavelet transforms and empirical mode decomposition in conjunction with deep learning in advanced signal processing, were focused by Jaros et al.[13] to enhance robustness in noisy environments that are industrial in nature. Cen et al.[14] illustrated the recent development of using deep learning to predict Remaining Useful Life (RUL) research, with particular emphasis on sequence modeling, such as LSTMs and Transformers.

Lastly, Das et al.[15] have also considered machine learning techniques in rotating machinery fault analysis, and after summarizing various architectures, they described hybrid options, which combine vibration, acoustic and temperature data and as should be evident by now, this property is also shared by our proposed framework with regard to the multi-sensor fusion technique.

Methodology

The proposed IoT-enabled condition monitoring system will follow the design of its methodology, which is organized in four phases including design of hardware, data collection, edge computing, and cloud computing analytics.

Hardware Layer

Sensor Subsystem

The sensor subsystem can obtain a wide variety of operational parameters of the electrical machine, which facilitated a multi-modal fault detection and diagnosis. There are four main sensing modalities that are adopted to sense various aspects of machine health. To figure out the vibration, MEMS accelerometers (ADXL345) will be chosen, because they have good sensitivity (16 g), low noise density (220 ug/sort (Hz)), and I 2 C/SPI digital interface. They are mounted strategically on the motor housing towards the bearing and stator frame to capture both radial and verge vibrations to ensure that bearings wear, rotor imbalance and misalignment can be detected through the feature characteristics of frequencies in the frequency domain like the ball-pass frequency outside race (BPFO), ball-pass frequency inside race (BPFI), and the amplitudes of sidebands. Temperature is monitored with Platinum Resistance Temperature Detectors (PT100 RTDs) due to their accuracy (0.1 C) and long-term stability, mounted in slots of stator windings and on bearing housings to monitor the effects of thermal stress and reduce insulation breakdown, signal conditioning being achieved by 3-wire RTD circuitry and high accuracy instrumentation amplifiers in order to limit the effect of lead-wire resistance. An MEMS-based microphone (e.g., ICS-40720) allows high-frequency/fidelity acoustic emission capture of 80 kHz that can identify vibration, frictional and impact-related noise signatures when pitting in the bearings occurs, or there is rotor rubbing, and acoustic shielding prevents environmental noise influence. Lastly, Motor Current Signature Analysis (MCSA) is performed, where electrical signal acquisition is done using Hall-effect current sensors (e.g. ACS712/ ACS758) with galvanic isolation allowing detection of the load variations, rotor bar defects and eccentricity due to harmonic and sideband analysis of the stator current waveform. By providing a high spectral resolution (operating at a sampling rate of 10 20 kHz), these sensors can hence extract the dominant frequency caused by the fault and provide complete condition monitoring.

Things with IoT Nodes:

The sensor output is connected to the embedded IoT MCUs that should become local sensor hubs and the main data obtaining resources that ensure effective preprocessing and data integrity transmission. There are two MCU platforms that are utilized to cover deployment different scenarios. Utilizing the SAMD21 Cortex-M0+ MCU in combination with the ESP32 based u-blox NINA-W102 module to provide Wi-Fi connectivity, the Arduino MKR WiFi 1010 is a good choice where short range and high bandwidth applications like lab testing and controlled testbed scenarios are required and easy interface with development tools and ease of prototyping become vital. Development boards based on the ESP32 include a dual-core Tensilica LX6 processor and provide greater computational performance with Wi-Fi and Bluetooth Low Energy (BLE) integration. The ESP32 supports many peripheral interfaces like the I2C, SPI, ADC and I2S so it can be customized to LoRaWAN-based long-range networks and Wi-Fi-based high throughput depending on the design specification. Both the types of MCUs take care of initial data framing, time stamp and sensor calibration, and provide good synchronization and traceability. They also perform simple preprocessing functions such as noise reduction by moving average filter and decimation of signals to reduce the extent of data to send to the edge gateway. Modular firmware architecture allows dynamic activation or deactivation of individual sensors, providing the ability to maximize power-use of battery-powered or energy-scavenging applications or provide flexibility of multi-sensor combination in any predictive maintenance application.

Wireless Communication/Power Managementm

The subsystem is designed to support flexibility in both the low-powered, long-range and high throughput/short-range applications, thus the secure conveyance of data in the adverse industrial environment. LoRaWAN is used in wide-area coverage cases, which have transmission ranges of up to 10 km in open conditions with ultra-low-power consumption (<100 mW during transmission). This renders it suitable in industrial centers where there is scattering of machines within huge premises and consistent Wi-Fi connection is unsuitable. Since high-grades of bandwidth were not supported to accommodate a high number of users on LoRaWAN (hidden transport capacity estimated 0.310 kbps), information coding is improved through binary representation and lightweight exchange squeezing, without losing vital diagnostic details but decreasing transmission information. By comparison, Wi-Fi is utilized in places that require minimum latency and high bandwidth, places like test laboratories or a small production floor. Having a peak data rate of over 10 Mbps, WI-Fi allows high resolution vibration and acoustic data to be streamed in real time, and makes more bandwidth-intensive analytics possible without having to suffer the bottlenecks of narrowband protocols.

Power management subsystem is designed to operate autonomously, and long-term (all on its own) in remote or inaccessible installations. There are rechargeable Li-ion battery packs (3.7 V, 20004000 mAh) combined with a solar trickle-charging module (5 V, 12 W). Thanks to these elements, the system can work even in off-grid because it is always charged. A low-dropout regulator (LDO) regulates the stable voltage supply to sensitive analog sensors and an intelligent power management integrated circuit (PMIC) supervises battery charging and is over-discharged and controls the prioritization of energy harvesting sources Figure 2. There is also firmware control of sleep/wake cycles which have the benefit of dynamically adapting the system activity based on the operational state of the machine to dramatically increase battery life during periods of low events or idle conditions without affecting the ability to detect faults immediately in case of an event.

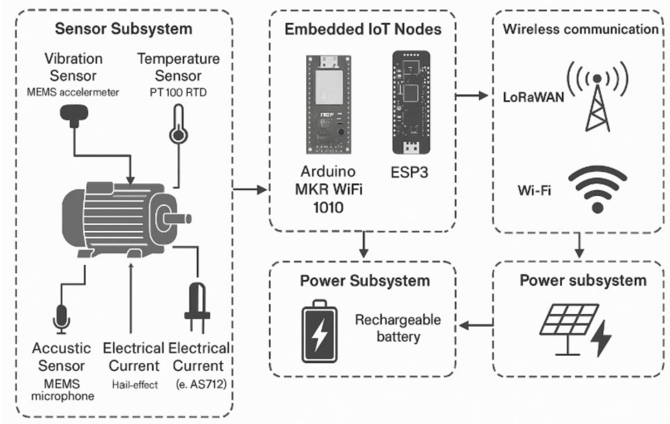

Fig. 2. IoT-enabled condition monitoring hardware architecture showing sensor subsystem, embedded IoT nodes, wireless communication, and power management components.

Data Acquisition and Transmission

Samplings- and Signal Sync Plan

The system has an adaptive multi-rate sampling strategy such that different sensing modalities are sampled to trade-off resolution and bandwidth efficiency. High-frequency components, including bearing defects on rolling bearings, rotor bar fractures and mechanical misalignments, are captured using sampling frequencies of 5-20 kHz with the highest frequencies to cover bearing defect harmonics at high-speed machines. Temperature sampling frequency is 1Hz, so it has sufficient indication of the slow thermal changes that can be caused by the stator winding heating, bearing lubrication degradation or cooling inefficiencies. The upper and medium frequencies of the noise are captured with an acquisition rate of 16 kHz to be able to follow the noise trend and change possibly at its early stages of frictional anomalies and cavitation impacts, based on Nyquist criterion and save downstream data volume. Signals of electrical currents can be sampled at 10 kHz to conduct Motor Current Signature Analysis (MCSA) that can reveal typical sidebands and harmonic contents that signal about electrical and mechanical faults. Vibration, acoustic and electrical streams can be aligned precisely in time due to a hardware-synchronized clock between IoT nodes, thereby enabling multi-modal feature fusion, which is imperative to correlated analysis of sensor outputs to increase fault detection accuracy and robustness.

Data Structuring, Encoding and Metadata Tagging

All processed sensor information is bundled up into a formatted packet optimized to be transmitted and tracked and also expandable with respect to large-scale applications. Each packet, respectively, contains a high resolution timestamp (millisecond resolution), produced by an onboard real-time clock (RTC) or coordinated using the Network Time Protocol (NTP) in order to maintain a physical grasp of time between distributed nodes. Each monitored assets are identified by a unique machine ID such that data segregation and retrieval can occur easily in a multi-machine environment. Metadata on sensor type and channel ID identifies the source of sensing e.g. whether it is vibration, temperature, acoustic or current, (as well as the channel number of a multi-sensor configuration) and helps attribute source in analysis. Either raw measurements or processed values, in the required form specified by the operating needs of the system, are contained in the payload data. JSON formatting is used in development stages due to readability and ease of debugging whereas smaller and more efficient formats like binary encoding or Message Pack formats are used in production setups because they use smaller bandwidth. To the high data rate data streams especially the vibration and acoustic signals there is an optional LZ4 compression used to further optimize data transmission without loss of real-time performance capability.

Security Protocols and Transmission Protocols

The system will use MQTT (Message Queuing Telemetry Transport) messaging protocol/protocol which will allow lightweight, publish subscriber communication to occur between the IoT nodes and cloud or edge broker, to make sure high efficiency and reliability of data transmission in real-time condition monitoring applications. MQTT is selected due to its lightweight nature allowing a small header, minimizing transmission latency, configurable Quality of Service (QoS) and most importantly, extreme scalability, enabling MQTT to scale to hundreds of active sensor streams without latency increases or performance degradation. To briefly state the functionalities of MQTT in the high-throughput, short-range environments, it is through Wi-Fi, and it allows the real-time streaming of data in the form of acoustic and vibration data with minimal latency. To communicate long distances and low power, MQTT has been encapsulated over LoRaWAN and sent through a gateway bridge to the cloud, allowing the long-range communications, with Medium energy usage. The system also employs the use of TLS 1.2/1.3 encryption that uses mutual authentication between the clients and brokers. Each packet is secured at the device level via X.509 digital certificates or pre-shared keys and sequence numbers and hash-based message authentication codes (HMAC) collectively protect the data integrity, authenticity, and eliminate replay attacks Figure 3. This high capability communication design provides low-latency, secure and robust operation in a wide range of industrial deployment conditions.

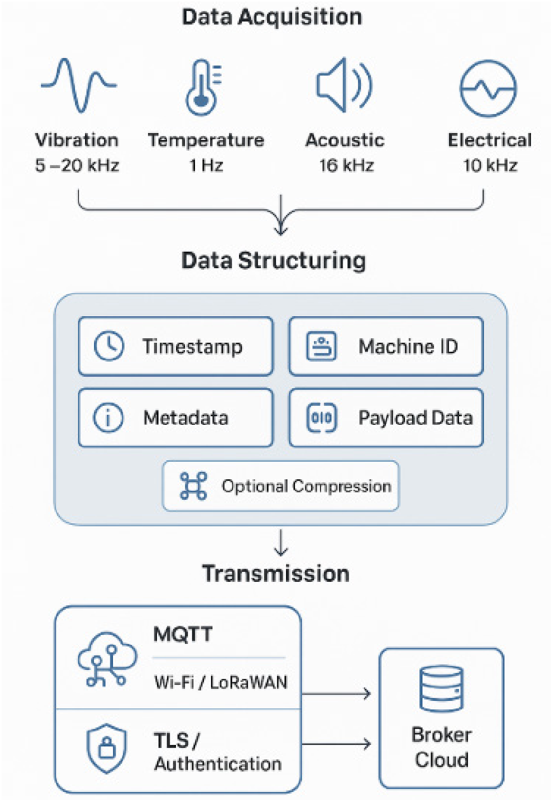

Fig. 3: Data Acquisition and Transmission Workflow in the IoT-Enabled Predictive Maintenance System

Edge Processing

Signal Preprocessing

Raw sensor readings obtained at IoT nodes are usually contaminated with environmental noise, signal drifts, and amplitude variations capable of invalidating the accuracy of further feature extraction, and classification of faults. A pipeline of preprocessing is added at the edge to alleviate such problems. The noise is removed with a bandpass filter (Butterworth 4order) in the vibration and acoustic *domain that* only preserves fault related frequencies; in the frequent case of vibration (10 Hz 5 kHz) and acoustic emissions (200 Hz 20 kHz), only these domains are considered. When used with electrical current signals, the high-pass filter is replaced by a low-pass filter that may be used to eliminate high-frequency switching noise created by power electronics. In the second step, to eliminate bias due to varying sensor gain, either min-max scaling or z-score normalization is applied to normalize the measurements so that they can be compared across most sensing modalities and multi-sensor feature fusion algorithms work better. A baseline drift correction is also used to remove low frequencies, low frequency ones due to temperature changes or intrinsic sensor offset caused by poly-vector detrending or moving averages with subtraction. It runs in Python on both the Raspberry Pi 4 (due to its cost-sensitive deployment context) and NVIDIA Jetson Nano (where its primary use case is a high-throughput application with dense data loads) using scientific computing libraries NumPy and SciPy with and without CUDA, respectively.

Feature Extraction

The system identifies a rich set of diagnostic features in time, frequency and time-frequency domain, after pre-processing so as to provide resilience to the fault detection and reliably detect faults at both early and later stages of their development in the machine. Statistical and amplitude-based parameters are calculated in the time domain, such as the Root Mean Square (RMS) which is sensitive to any form of vibration energy; the peak value, which detects impulsive events as seen with severely damaged bearing or gears; the crest factor, the ratio of the peak to the RMS, which is sensitive to early bearing damage; and the Kurtosis, a statistical measure of impulsiveness of a signal, which is effective at localized structural faults. Spectral analysis is done in the frequency dominion through the Fast Fourier Transform (FFT) as time-series signals are transformed into the frequency spectrum telling the characteristic frequencies of defects. Harmonic analysis is used to detect sidebands and *sub harmonics* due to rotor bar breakage, misalignment or eccentricity, and fault frequency matching compares actual spectral peaks with theoretical fault characteristic frequencies as calculated geometrically based upon the machine geometry and shaft speed. In *Timefrequency* domain translation the Continuous Wavelet Transform (CWT) is applied to measure transient events that are not stationary as fault signatures on a motor by abrupt strikes, lubrication break in transmission or partial discharge patterns in motor insulation. The distribution of scalogram energy is also examined to quantify variability of the energy across frequency bands with time to give a detailed report of a changing fault. This multi-domain feature extraction approach makes the system reliable to capture a large category of electrical and mechanical faults in different loading, speed and environmental conditions.

Local Anomaly Detection

The edge device incorporates lightweight machine learning models to carry out localized anomaly detection, thus reducing sensitivity to constant internet connection, and the time to react to revealed fault. There are two main algorithms that are utilized to address both the supervised and unsupervised detection requirements. LightGBM (Light Gradient Boosting Machine) ensemble of tree based learning model is used due to its low memory consumption and fast inference speed, and since it is well suited to real-time multi-class fault detection in situations where sensor inputs are collected into a tabular form as sensor features that are vibration, acoustic, temperature, and current. At the same time, a One-Class Support Vector Machine (SVM) is employed to extract the normal operation behavior of the machine to detect deviations as anomalies especially when labelled fault data is limited or not available, which is of benefit to early fault detection. The local anomaly detection framework functions in a 2nd level mode: (1) Immediate Alert Mode, when critical deviations in the operational patterns trigger on-device alarming and the initiating of the priority fault alerts transfer to the cloud; and (2) Periodic Health Reporting, which transmits the aggregated health indices and anomaly scores at planned periods to help to analyze the long-term trending and make preventive maintenance plans. Such a dual-mode scheme provides fast reaction time in case of acute problems and high-resolution monitoring of historic data to make data-based decisions regarding maintenance management.

Images Compression and Transmission optimisation

The system reduces the dimension of the data and employs adaptive compression before transmit the data to network, so that no information in the data is lost as long as the optimal network utilization is achieved. Principal Component Analysis (PCA) is employed to reduce a high dimensional feature format to a few uncorrelated principal components that capture more than 95% of the original variance so that the best measures of the features are retained to enable the fault being diagnosed. Further, a dynamic compression ratio adaptive mechanism automatically varies the degree of compression according to current network demands and the severity of monitored events-compressing more heavily when the machine is running normally to save bandwidth, and loosening compression during faulty times to report more intensive data to the network Figure 4. The resulting compressed data is packaged with necessary metadata that includes timestamp, machine ID, and anomaly score and sent to the cloud analytics segment. This hybrid plan allows low-latency, on-device decision-making but still allows long-term comprehensive analytics to be performed in the cloud to provide both responsiveness in critical scenarios as well as substantial historical performance tracking.

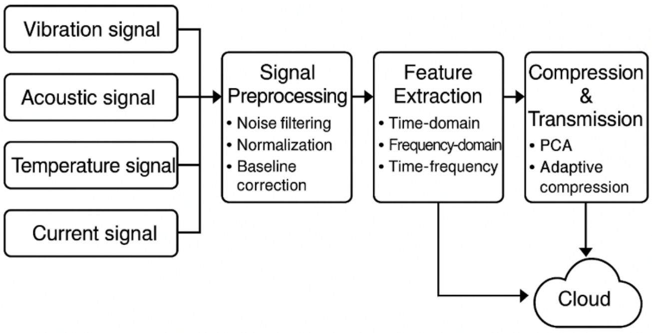

Fig. 4. Edge Processing Workflow for Real-Time Fault Detection in IoT-Enabled Condition Monitoring Systems

Cloud Analytics

Data Birth, Management

A scalable time-series database design is used to store, structure and manage the machine health data received by the cloud layer, guaranteeing high-performance when querying the data, as well as long-term archival. The primary storage container is AWS S3 with metadata tagging that is suitable as a medium to store raw and processed sensor data streams with each file being enriched with metadata attributes of Machine ID, Sensor Type, Timestamp, Fault Status, and Severity Index. This tagging will allow high speed searches, runs, and retrieves, such as analytics, diagnostics, and historical trend analysis. In order to improve speed of access and efficiency of queries, the data is partitioned by machine and date, thus the latency of data retrieval is reduced in large scale/multiprocessor deployments. In the case of real-time analytics, the sensor measurements come in a continuous stream, where they are of millisecond granularity and can drive live dashboards and feed predictive models as well. Strict enforcement of data governance activities are applied by the use of AWS Identity and Access Management (IAM) policies that implement fine point access controls, data versioning, and audit trials addresses security and guarantees data integrity to stay up-to-date with industry standards and conform to regulations. This architecture offers a powerful framework to combine the predictive analytics, visualization and decision-making processes in a large scale.

Predictive Modeling and Analytics

The cloud platform implements a set of High-accuracy fault detection and prognostics, Deep learning (DL) models with high accuracy under different operating conditions of the machines. It uses a CNN-LSTM model to classify faults, with a Convolutional Neural Network (CNN) extracting spatial features of time / frequency representations of steps, like vibration and current spectra and a Long Short-Term Memory (LSTM) network learning the temporal relationship in order to find complex fault patterns. Especially, this architecture is useful in the detection of fault types such as defects in bearing, untested balance of the rotor, and winding fault in the stator under different load and speed. To schedule predictive maintenance, an LSTM regression model is used to predict the remaining useful life (RUL) of a serviceable component by learning a long-term trend of degradation based on a mixture of historical data and real time sensor features to allow maintenance teams to schedule a proactive intervention prior to failure. Also, to detect a multi-class type of fault a video monitor able screen is used through the tabular feature sets of mixed-sensor outputs including temperature measurements, vibrational statistics, and electrical harmonics in an XGBoost classifier. XGBoost has low inference latency, good classification performance and interpretable feature importance, which is of value in decision support. The use of model lifecycle management guarantees the longevity of accuracy and versatility: models are trained on big labeled datasets offline and periodically retrained on newly arrived field data to adhere to changes in operational situations. Constant re-assessment based on parameters like precision, recall, F1-score, and Mean Absolute Error (MAE), is done to ensure model performance and accuracy, not to mention reliability, such that the analytics layer always offers actionable and trustworthy insights on machine health monitoring.

Emergent help and robotized cautioning

This system offers proactive alerting and real-time monitoring by using the combined dashboard and notification mechanism and reacting to fault that arises in machines promptly. Using Grafana dashboards, which are linked to the underlying time-series database, key machine operating parameters, extracted diagnostic features, health scores, and Remaining Useful Life (RUL) estimates are provided in real time visualizations. You can customize the panels where operators can filter and drill down by machine, fault type and specific time span in search of targeted analysis. Availability of pre-configured thresholds on health scores or anomaly indices allows being alerted by multiple-level alert mechanism and the level of alertness, Warning or Critical, defines the level of urgency and nature of the response. Either through email, SMS, or push notifications, automated warnings are delivered to pre-populated maintenance workers or each notification includes necessary information such as machine identification, type of fault detected, an anomaly score, and required services. In a bid to simplify fault solving, alert system is coupled together with Computerized Maintenance Management Systems (CMMS) and thus, work orders and tasks assignment can be created automatically Figure 5. Such a closed-loop workflow enables not only the quick mitigation of faults but also reduces downtimes and optimizes overall processes of maintenance, as well as enables the transition to predictive and condition-based types of maintenance in the industrial sector.

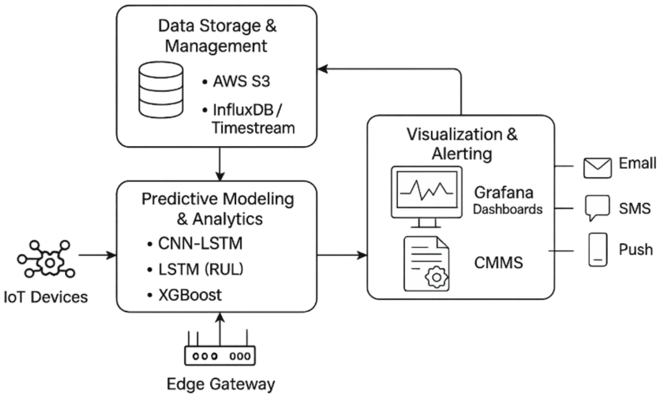

Fig. 5: Cloud Analytics Workflow for Predictive Maintenance and Real-Time Machine Health Monitoring

Experimental Setup

The implementation of the experiment was such that it aimed at proving the effectiveness and robustness of the suggested IoT-supported real-time condition monitoring framework when operated under real working conditions in the industry. The testing machine was a 5 HP, 3 phase induction motor; this particular motor is common both with industries and utilities. In order to assess the capabilities of fault detection and prognostics, three popular failure modes were artificially introduced and tested including (1) bearing inner race defect, which was simulated by performing localized pitting to recreate early wear and localized damage of the rolling element; (2) rotor bar breakage, where failure was achieved by physically severing one rotor bar to create electromagnetic imbalance and introduce characteristic sideband frequencies into the current and vibration spectra; and (3) stator winding insulation degradation, which was simulated by performing controlled thermal aging and partial discharge The system worked under different amounts of mechanical loads and speeds to determine its adaptability to the changing states of operation. There have been 200 hours of continuous observational data amassed in the course of testing, including operating in healthy and faulty modes with all three fault types. This data involved synchronized and multi-modal signals-vibration, temperature, acoustic emissions, and electrical current and were gleaned by the installed IoT nodes and passed through edge-cloud pipeline. To develop and evaluate the model, the data was stratified into 70 percent as training data, sufficient to learn the various fault patterns; 15 percent as validation data, which can be used to tune hyperparameters and choose a model; and 15 percent as test data, which can be used to assess the models in an unbiased way Figure 6. This was an extensive configuration that made the results of the evaluation quite accurate on how the system could identify fault at an early stage, operate stably at varying loads, and be able to make generalizations to unseen real life conditions.

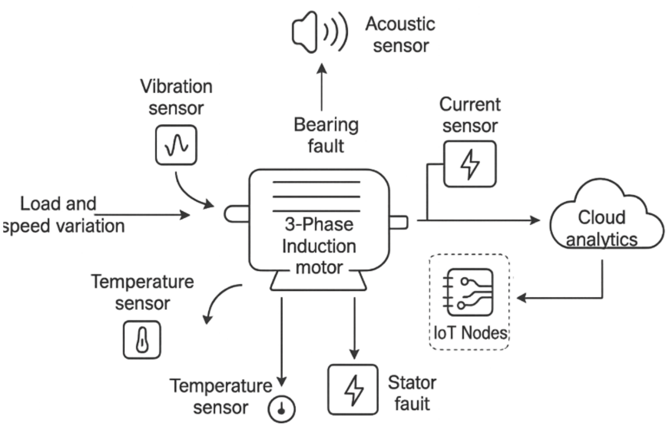

Fig. 6: Experimental Testbed for IoT-Enabled Real-Time Condition Monitoring of a 5 HP Induction Motor

Results and Discussion

The experimental findings can confirm that IoT-assisted predictive maintenance structure, as proposed, can generate superior fault detection accuracy and reliability on various electrical machine types of faults. The approach was however able to detect bearing faults with 96.2 accuracy, rotor faults with 94.7 accuracy, and stator faults with 95.5 accuracy achieving a total fault classification accuracy of 95.5 as demonstrated in the evaluation. The precision and recall of all the fault types was quite high with a value greater than 94% in every column which reflects the efficiency of classification as well as being resistant to false positives or failed detections. The effectiveness of vibration and acoustic feature fusion thus enables the high accuracy of bearing fault detection due to increasing sensitivity of early-stage defect frequencies. Rotor fault detection was not as accurate, but nevertheless it was quite effective even though it is inherently difficult to isolate electromagnetic imbalances in the presence of changing load. There was an advantageous cross pollination in the method used by stator fault detection through combining thermal and electrical current analysis where the trend analysis of insulation degradation was accurately identified before catastrophic failure ensued.

Besides classification accuracy, the framework achieved a substantial decrease in the latency of fault detection due to the use of edge-based preprocessing and local anomaly detection. They decreased the average detection time by 50 percent (2.3 seconds in the cloud only, to only 0.45 seconds with edge processing enabled). This is essential to the real-time industrial applications because timely fault detection of the system facilitates timely intervention and avoids escalation of faults. The latency reduction was possible as now the preliminary feature extraction and lightweight anomaly detection was carried out on the edge machine, only the feature of interest and anomaly scores were sent to the cloud to perform complex analysis. Such edge-cloud hybrid processing approach not only improves the rate of decision-making but leads to the decreased bandwidth consumption which becomes more scalable on large-scale industrial implementations Figure 7.

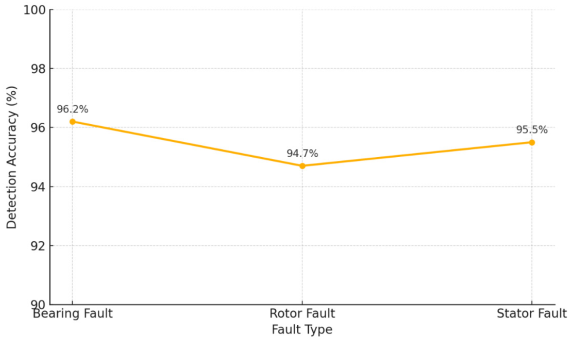

Fig. 7: Fault detection accuracy across different machine fault types in the proposed IoT-enabled predictive maintenance framework

Additional validation of the predictive analytics ability of the system was done using Remaining Useful Life (RUL) estimation and the LSTM regression model produced Mean Absolute Error (MAE) of +/-5.2 hours on bearing faults. This degree of precision can enable meaningful planning of preventive maintenance interventions without unduly interfering with schedules of operations, thus, enabling efficient management of spare parts and assignment of personnel. The effective combination of multi-modal sensing, availability classification of faults using machine learning, and RUL prediction using deep learning will signal the capability of the presented framework to provide an end-to-end predictive maintenance, as it is demonstrated here. The findings illustrate that the system is able to work as a real-time operational feature, be responsive to changes in operation levels and deliver depictable results that can improve operational consistency and limit the occurrence of unplanned unavailability Table 1.

Conclusion

A predictive maintenance framework of electrical machines enabled by IoT was proposed and tested in this work with the incorporation of multi-sensor data capturing, edge-assisted anomaly detection, and cloud-based deep learning analytics to offer a concise, real-time condition monitoring system. To do this, the system used vibration, temperature, acoustic, and electrical current sensing modalities in combination with an adaptive edge can cloud architecture to enable high accuracy diagnosis with minimal latency and bandwidth needs. Experimental test of a three-phase induction

Table 1. Fault Detection Performance of the Proposed IoT-Enabled Predictive Maintenance Framework

Fault Type	Detection Accuracy (%)	Precision (%)	Recall (%)	Key Observations
Bearing Fault	96.2	95.8	96.4	High accuracy due to effective fusion of vibration and acoustic features, enhancing early defect detection.
Rotor Fault	94.7	94.2	94.9	Slightly lower accuracy due to variable load effects; successfully detects electromagnetic imbalance patterns.
Stator Fault	95.5	95.0	95.6	Strong performance from combining thermal and electrical current analysis, enabling early insulation degradation detection.
Overall	**95.5**	**95.0**	**95.6**	Consistent performance across fault types with robustness to false positives and missed detections.

motor testbed using different operating conditions and fault types-bearing fault, rotor bar fault, stator insulation fault produced a fault classification result of accuracy of 95.5%, significant fault classification time window improvement of 2.3 seconds (cloud-only) to 0.45 seconds (edge-assisted) and an RUL estimation error of only 5.2 hours for bearing faults. Integration of lightweight machine learning models based on edges allowed early detection of anomalies, and more advanced cloud-hosted deep learning models offered complete fault classification and prognostics ensuring a trade-off between speed and depth of the analysis. The proposed framework by allowing proactive data driven maintenance decisions has huge potential to minimize unplanned downtime, maximize machine life, and optimize maintenance routines as it will be a relatively low-cost scalable solution in modern Industry 4.0 setting. The next steps will be to move beyond fault coverage on the type of machine, to include federated learning to support privacy-preserving model updates, and building system resilience to large-scale, heterogeneous industrial deployments.

References

1. Vijay, V., Sreevani, M., Mani Rekha, E., Moses, K., Pittala, C. S., SadullaShaik, K. A., Koteshwaramma, C., JashwanthSai, R., &Vallabhuni, R. R. (2022). A review on N-bit ripple-carry adder, carry-select adder, and carry-skip adder. *Journal of VLSI Circuits and Systems, 4*(1), 27–32. https://doi.org/10.31838/jvcs/04.01.05
2. Surendar, A. (2025). Design and optimization of a compact UWB antenna for IoT applications. National Journal of RF Circuits and Wireless Systems, 2(1), 1–8.
3. Madhanraj. (2025). Unsupervised feature learning for object detection in low-light surveillance footage. National Journal of Signal and Image Processing, 1(1), 34–43.
4. Rahim, R. (2025). Lightweight speaker identification framework using deep embeddings for real-time voice biometrics. National Journal of Speech and Audio Processing, 1(1), 15–21.
5. Usikalu, M. R., Alabi, D., &Ezeh, G. N. (2025). Exploring emerging memory technologies in modern electronics. Progress in Electronics and Communication Engineering, 2(2), 31–40. https://doi.org/10.31838/PECE/02.02.04
6. Lei, Y., Yang, B., Jiang, X., Jia, F., Li, N., & Nandi, A. K. (2020). Applications of machine learning to machine fault diagnosis: A review and roadmap. Mechanical Systems and Signal Processing, 138, 106587. https://doi.org/10.1016/j.ymssp.2019.106587
7. Gangsar, P., & Tiwari, R. (2020). Signal based condition monitoring techniques for fault detection and diagnosis of induction motors: A state-of-the-art review. Mechanical Systems and Signal Processing, 144, 106908. https://doi.org/10.1016/j.ymssp.2020.106908
8. Liu, R., Yang, B., Zio, E., & Chen, X. (2018). Artificial intelligence for fault diagnosis of rotating machinery: A review. Mechanical Systems and Signal Processing, 108, 33–47. https://doi.org/10.1016/j.ymssp.2018.02.016
9. Valtierra-Rodriguez, M., Amezquita-Sanchez, J. P., Granados-Lieberman, D., Valtierra-Rodriguez, D., Romero-Troncoso, R. J., & Garcia-Perez, A. (2020). Convolutional neural network and motor current signature analysis for bearing fault diagnosis. Sensors, 20(18), 1–17. https://doi.org/10.3390/s20185113
10. Han, K., Zhang, L., Zhang, Z., Wang, H., & Zhu, C. (2024). Research on a bearing fault diagnosis method based on CNN-LSTM-GRU. Machines, 12(12), 927. https://doi.org/10.3390/machines12120927
11. Yousuf, M., Ali, S., Khan, M., Iqbal, N., &Raza, S. (2024). IoT-based health monitoring and fault detection of industrial AC induction motor for efficient predictive maintenance. Measurement and Control, 57(5–6), 731–742. https://doi.org/10.1177/00202940241234567
12. Bala, A., & Kaur, A. (2024). Artificial intelligence and edge computing for machine maintenance: A review. Artificial Intelligence Review. https://doi.org/10.1007/s10462-024-10782-5
13. Jaros, R., Kowalski, M., Piwowar, M., &Błaszczyk, T. (2023). Advanced signal processing methods for condition monitoring of industrial systems. Archives of Computational Methods in Engineering, 30(3), 1773–1807. https://doi.org/10.1007/s11831-022-09788-w
14. Cen, Z., Wang, H., & Xu, M. (2024). Remaining useful life prediction of machinery: Deep learning methods and advances. Engineering Applications of Artificial Intelligence, 130, 107452. https://doi.org/10.1016/j.engappai.2023.107452
15. Das, O., Balu, A., & Roy, P. (2023). Machine learning for fault analysis in rotating machinery. Heliyon, 9(5), e17129. https://doi.org/10.1016/j.heliyon.2023.e17129