

IoT-Enabled Electrical Signature Analysis for Predictive Maintenance of Industrial Motors: A Review of Hybrid Time-Series Approaches

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Abstract: Industrial motors underpin pumping, cooling, conveying and many manufacturing operations; deterioration can interrupt production, raise maintenance costs and increase energy use. This narrative review examines the role of electrical signature analysis combined with industrial Internet of Things (IOT) monitoring in predictive maintenance. It synthesizes measurement of voltage, current, power-quality variables and harmonics; edge-side data checks and telemetry; and time-series methods for identifying departures from expected behaviour. Prophet-style forecasting can represent trends and recurring patterns, while Long Short-Term Memory (LSTM) models can analyse sequences of forecast residuals. The review also considers current-signature analysis, phase imbalance, data quality, cybersecurity and maintenance decisions. A supplied 2026 preprint reports an industrial case involving two cooling-group motors and compares rule-based alarms with a hybrid Prophet–LSTM detector [1]. Its numerical results are reproduced only as results reported by that preprint; they were not independently measured, audited or replicated for this review. The wider literature is used to contextualize motor-fault diagnosis, measurement practice, IOT analytics and maintenance planning [2] [15]. Reliable application requires calibrated instrumentation, representative validation, transparent alerts and technician confirmation.

Keywords: Predictive maintenance, Industrial IOT, electrical signature analysis, induction motors, harmonic distortion, phase imbalance, time-series forecasting, LSTM

I. INTRODUCTION

Industrial motors are widely used in pumps, fans, compressors, conveyors, and cooling systems. Their condition influences equipment availability, product quality and energy use. Faults may develop because of bearing wear, rotor defects, insulation deterioration, voltage unbalance, loose terminals or changes in the driven load. Monitoring electrical quantities can provide useful clues about such changes because voltage and current are closely linked to the motor's operating state [2], [4], [12], [13].

Maintenance strategies are commonly grouped into corrective, preventive and predictive approaches. Corrective maintenance takes place after a fault has occurred and may lead to costly interruptions. Preventive maintenance follows a calendar or operating-hour schedule, but can result in unnecessary servicing when equipment condition is still acceptable. Predictive maintenance instead uses condition information to identify deviations from normal behaviour and support maintenance planning [5], [10], [11]. Its value depends on the quality of measurements, the ability to distinguish faults from normal load changes, and the usefulness of the resulting alerts.

Industrial IOT systems can connect sensors, embedded devices, and analytical services to enable continuous monitoring [6]. However, collecting data alone does not produce a dependable diagnosis. Data must be time-aligned, screened for errors, and interpreted in the context of operating conditions. This review focuses on the combination of electrical



signature analysis and hybrid time-series methods as a practical route toward earlier fault indication in industrial motors.

II. OBJECTIVES OF THE REVIEW

1. Explain the role of electrical measurements in motor condition monitoring.
2. Describe a practical IOT data pathway from measurement devices to maintenance alerts.
3. Review the complementary roles of trend forecasting and sequence-learning methods.
4. Summarize the source article's reported industrial observations without presenting them as new experiments.
5. Identify limitations and good practices for validating predictive-maintenance systems.

III. REVIEW METHODOLOGY

This paper adopts a narrative literature-review approach rather than reporting a new experiment or a systematic database search. The supplied preprint [1] is treated as the principal case source for the specific monitoring architecture and numerical observations discussed in Section 7. Fourteen additional publications and standards are used to frame measurement methods, induction-motor diagnosis, predictive-maintenance planning, IOT data pipelines, forecasting, sequence learning and power-quality practice [2], [15]. The evidence is organized around electrical measurements, monitoring architecture, anomaly detection, reported case observations, and implementation gaps.

No new motor measurements, model training or experimental trials were conducted for this review. Accordingly, case-specific numbers are explicitly attributed to [1], which is a preprint rather than an independently verified experiment from the present authors. Metrics copied from that source should be interpreted in the context and under the assumptions of its reported evaluation; they do not establish expected performance at another plant, for another motor type, or under a different operating regime.

IV. ELECTRICAL SIGNATURE ANALYSIS FOR MOTOR MONITORING

4.1 Electrical Parameters and Their Diagnostic Value

A motor-monitoring installation may record RMS voltage and current, active and reactive power, power factor, frequency, phase-current imbalance and total harmonic distortion (THD). These variables help describe electrical loading and power quality. Trends are often more informative than isolated readings: a persistent change in current, an increase in selected harmonic components or a growing difference between phase currents may justify further inspection [2], [4], [12], [13]. The interpretation must account for changes in process load, motor speed, drive settings, and supply conditions.

Electrical signature analysis examines the characteristics of measured electrical signals to identify patterns associated with equipment condition. Motor-current signature analysis has been studied for induction-motor fault detection, including rotor-related and other Electromechanical abnormalities [12], [13]. Nevertheless, electrical signatures are not unique to one fault. For example, current harmonics can be influenced by power-electronic drives, nonlinear loads and supply distortion as well as by a motor's condition. Measurements should therefore be interpreted alongside operating history and, where appropriate, vibration, temperature or inspection evidence [2]–[4].

4.2 Measurement Quality and Standards

The reliability of a predictive-maintenance model begins with reliable instrumentation. Current transformers, voltage dividers, and power-quality monitoring devices must be selected for the expected range and installation environment. Calibration, suitable isolation, correct phase mapping, and synchronized timestamps reduce the chance that measurement errors will be mistaken for equipment faults. Power-quality measurement procedures provide a consistent basis for comparing voltage, current, and related quantities [15]. General condition-monitoring guidance also emphasizes defining the monitored asset, choosing suitable measurements and interpreting results within an established monitoring program [14].



Data validation should flag missing records, sensor saturation, implausible values, duplicated messages, and abrupt changes caused by device restart. When the data quality is uncertain, the system should label the affected period rather than generate a confident fault warning. This is particularly important when a model is sensitive to short-lived spikes or when the training data contain gaps.

V. IOT-BASED MONITORING ARCHITECTURE

5.1 Edge Acquisition and Communication

A practical monitoring pathway connects measurement, edge processing, communication, storage, and analytics. In the supplied preprint, a power-quality metering IC and an ESP32-class controller are described as the collection and communication hardware [1]. In a review-derived architecture (Fig. 1), the edge layer checks ranges, timestamps records, identifies missing or implausible values, and buffers data through temporary connection loss. Hardware choice must match the electrical installation, isolation requirements, and required measurement accuracy [2], [15].

MQTT can provide lightweight publish/subscribe telemetry between edge devices and analytics services, but protocol choice alone does not guarantee reliability. The implementation should preserve message ordering or timestamps, acknowledge or retry delivery where needed, handle disconnections, and protect credentials and data in transit. Each alert should remain traceable to the source measurements and asset configuration so a technician can audit its basis [6].

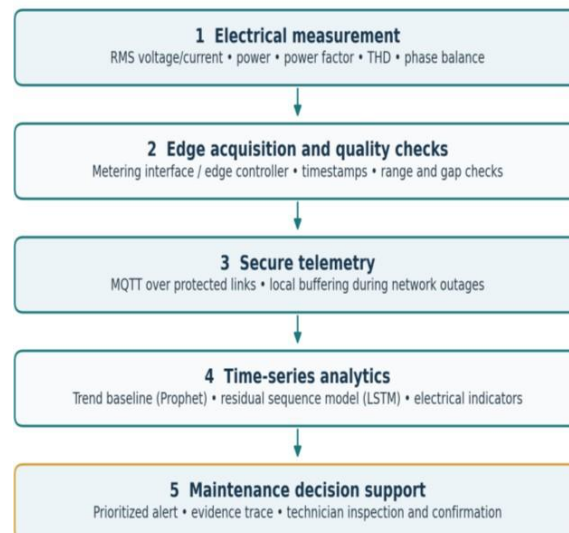


Fig. 1: Review-derived conceptual architecture for IOT-enabled electrical signature monitoring (authors' synthesis based on [1], [2], [6], [14], [15]).

5.2 Data Management and Cybersecurity

The monitoring platform should maintain a consistent data schema, document engineering units, and store configuration changes alongside the measurements. Asset identity, operating state, and maintenance history can help distinguish a real degradation trend from a change in duty cycle. Access control, authenticated devices, protected communication, and controlled firmware updates are also important because connected monitoring devices can introduce cybersecurity risks. These design requirements should be planned as part of the system rather than treated as optional additions [6], [10].



VI. HYBRID TIME-SERIES ANOMALY DETECTION

6.1 Baseline Forecasting with Prophet

Forecasting models estimate what a signal is expected to do under normal operating conditions. Prophet represents a time series using components such as trend, seasonality, and event-related effects [7]. This can be useful for industrial assets whose measurements change with work shifts, production cycles, or scheduled shutdowns. The difference between a measured value and its forecast is commonly called the residual. A large residual indicates that the observed behaviour differs from the estimated baseline, but does not by itself prove a fault.

6.2 Sequence Learning with LSTM

Long Short-Term Memory (LSTM) networks are recurrent neural-network models designed to learn temporal dependencies in sequential data. They can be used to predict upcoming values or residual patterns from a sequence of earlier observations [8]. In a hybrid approach, a baseline forecast is first used to capture broad trends and recurring patterns; an LSTM then models the residual sequence. The difference between the observed residual and the predicted residual becomes one possible anomaly indicator [1], [8].

6.3 Combining Indicators and Setting Alerts

A practical detector can combine forecast residuals with changes in electrical indicators, including total harmonic distortion (THD) and phase-current imbalance. The inputs should be normalized before combining them, and thresholds should be estimated from representative normal-operation data. A changed load, drive configuration or duty cycle may require reassessment of the baseline [1], [3], [9]. Figure 2 presents a conceptual hybrid workflow; it is not a claim that one thresh holding strategy is optimal for all assets.

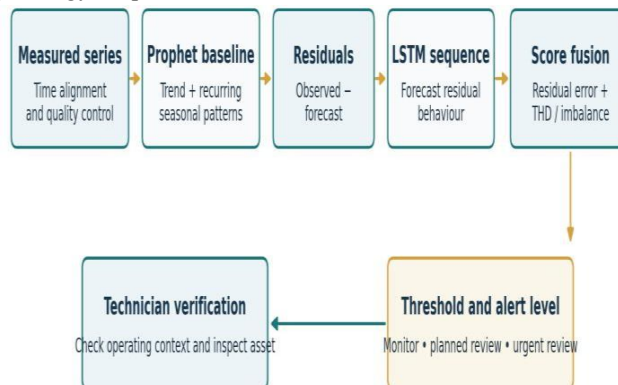


Fig. 2: Original conceptual workflow for hybrid Prophet-LSTM anomaly detection, synthesized from [1], [7] and [8].

An anomaly score is best treated as a decision-support signal. A warning should identify the affected asset, time window, variables that changed and the persistence of the deviation. Maintenance staff can then inspect the motor, connections, supply and driven process. This helps avoid treating every statistical outlier as a confirmed mechanical failure.

VII. INDUSTRIAL OBSERVATIONS REPORTED IN THE SOURCE

7.1 Monitoring Context

The supplied preprint describes a monitoring case involving two industrial cooling-group motors over a period that it characterizes as four months [1]. Voltage, current, power-quality indicators and phase imbalance were monitored, and the reported evaluation compared a hybrid Prophet-LSTM detector with a rule-based method. The observations below are a secondary summary of that preprint only; the present review did not collect the measurements or independently validate the fault interpretations.



7.2 Harmonic Trends and Phase Imbalance

For Motor A, the preprint reports current THD around 36% and voltage THD around 2%, alongside upward trends in the 5th and 11th current harmonics [1]. Those observations warrant investigation in the reported case, but they do not independently establish bearing or other mechanical damage. Harmonics may also reflect variable-frequency drives, nonlinear loads and supply characteristics; diagnosis should consider the measurement setup and corroborating inspection or sensor evidence [2], [4], [12], [13], [15].

For Motor B, the preprint reports phase-current imbalance between approximately 3.6% and 9.5%, while voltage imbalance remained below 0.8% [1]. The difference supports checking phase-specific loading, terminals, contactors and connections, but does not prove a loose connection by itself. A fault label should follow physical inspection and corroborating measurements rather than an anomaly score alone. Table 1 summarizes these source-reported observations.

Table 1: Selected motor observations reported in the supplied preprint [1]; not independently measured in this review.

Asset / indicator	Observation reported in [1] and interpretation
Motor A — current THD	Approximately 36%; reported alongside voltage THD near 2%. This indicates a power-quality condition to investigate, not a unique motor-fault diagnosis.
Motor A — 5th and 11th harmonics	Increasing trends are reported. The preprint associates them with possible mechanical concerns; independent inspection is needed before diagnosing a fault.
Motor B — phase-current imbalance	Approximately 3.6%–9.5%, while voltage imbalance stayed below 0.8%. This supports checking connections and loading, but does not prove a loose connection.

7.3 Reported Model Metrics and Energy Estimates

The supplied preprint reports accuracy, precision, recall and F1-score of 0.78, 0.69, 0.65 and 0.67 for its rule-based detector, and 0.94, 0.92, 0.90 and 0.91 for the hybrid Prophet–LSTM detector [1]. Its ablation table also reports LSTM-only scores of 0.81, 0.77, 0.75 and 0.76, and Prophet-only scores of 0.84, 0.78, 0.75 and 0.77, in the same metric order [1]. These reported values are summarized in Table 2 and visualized selectively in Fig. 3; they are reproduced for literature discussion and were not independently recalculated or validated in this review.

Table 2: Source-reported ablation metrics from [1]; values are reproduced as published and were not recalculated.

Method reported in [1]	Accuracy	Precision	Recall	F1-score
Rule-based detector	0.78	0.69	0.65	0.67
LSTM only	0.81	0.77	0.75	0.76
Prophet only	0.84	0.78	0.75	0.77
Hybrid Prophet–LSTM	0.94	0.92	0.90	0.91



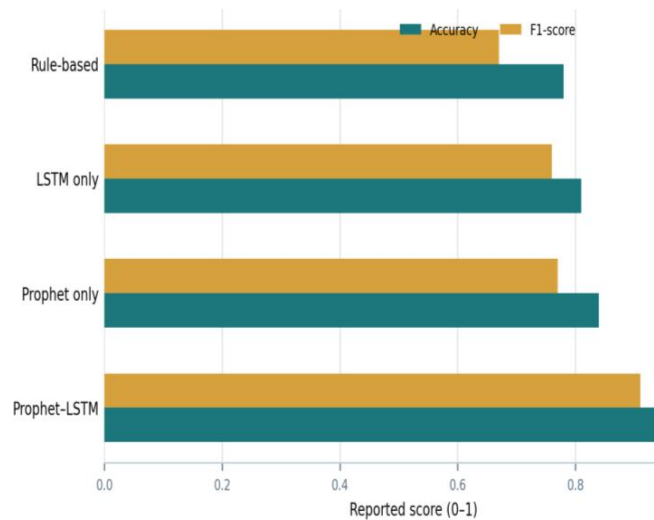


Fig. 3: Selected accuracy and F1-score values reported by the preprint [1].

The preprint estimates annual emissions of about 27.5 t CO₂-equivalent for Motor A and 12.0 t for Motor B, associating them with estimated energy losses of 5.2% and 2.8%, respectively [1]. The source suggests a passive filter for Motor A and connection revisions for Motor B. These are the source authors' estimates and proposals; this review has not recalculated the energy or emissions assumptions. Their applicability elsewhere depends on the load, operating hours, baseline and emission factor. Table 3 records the numbers with this limitation made explicit.

Table 3: Energy-loss, emissions and proposed-recovery estimates reported in [1]; assumptions were not independently recalculated.

Mot or	Reported condition	Energy loss	Annual CO ₂ -eq.	Source-proposed action / recovery
A	High current harmonics (current THD ≈ 36%)	≈ 5.2%	≈ 27.5 t	Passive filter; > 5.0%
B	Phase-current imbalance (≈ 3.6%–9.5%)	2.8%	≈ 12.0 t	Connection revision; ≈ 3.5%

VIII. COMPARATIVE DISCUSSION

The approaches differ in their balance of interpret ability, sensitivity and implementation effort. Fixed thresholds are easy to explain but can become unreliable when normal operating conditions shift. Electrical indicators remain physically interpretable, yet several different faults and load conditions can produce similar signatures. Prophet can represent trend and seasonality, while an LSTM can learn temporal dependencies; a hybrid can combine these roles but introduces additional data, tuning and validation requirements [1], [5], [7], [9]. Table 4 summarizes these trade-offs qualitatively.

Table 4: Qualitative comparison of approaches discussed in the reviewed literature.

Approach	Strength / role	Main limitation
Fixed-threshold rules	Transparent and easy to implement	Can miss slow drift or trigger on normal load changes
Electrical indicators	Physically interpretable measures (e.g., THD, phase imbalance)	Several operating conditions may produce similar signatures
Prophet baseline	Represents trend and recurring patterns	May not capture every short, nonlinear deviation
LSTM sequence model	Learns temporal dependencies from sequential data	Needs representative data, tuning and monitoring
Hybrid Prophet-LSTM	Combines a baseline with residual	More complex to validate, explain and maintain



	sequence analysis	
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The broader condition-monitoring literature emphasizes that successful maintenance programmes require more than a high model score. Measurement selection, baseline definition, diagnosis, reporting and maintenance planning must work together [10], [11], [14]. A model should be evaluated using precision and recall as well as accuracy because faults may be rare and missed detections can have a high operational cost. Performance should also be assessed across different operating periods and, where possible, at a separate site.

IX. RESEARCH GAPS AND FUTURE SCOPE

9.1 Wider Validation

Further work should include a larger range of motors, loads, drive systems, and industrial environments. Training and test periods should be separated chronologically, and reported metrics should identify how faults and normal periods were labelled. Cross-site evaluation would help determine whether a model learns general fault behaviour or merely memorizes the conditions of one installation [3], [5], [9].

9.2 Explain ability and Fault Confirmation

Maintenance staff need to understand why an alert was raised. Future systems should show which electrical variables changed, how long the change persisted, and how the observed signal differed from its expected baseline. Alert levels should distinguish monitoring, planned inspection, and urgent review, while retaining technician confirmation before a specific fault is recorded.

9.3 Robust Data and Secure Deployment

Research should test how the model responds to missing data, sensor drift, network interruptions, changed operating schedules and firmware updates. Edge processing can reduce communication latency, but it must be designed with adequate buffering, device identity and secure communication [6]. Consistent measurement procedures and condition-monitoring practices can support repeatable assessment across sites [14], [15].

9.4 Integration with Maintenance and Energy Management

A future system may link anomaly records with work orders, inspection results and component replacement history. With sufficient longitudinal data, it may also estimate degradation progression or remaining useful life. Energy analysis can be integrated where calibrated measurements support it, but maintenance improvement and energy savings should be reported separately unless a clear causal relationship is established [5], [10], [11].

X. CONCLUSION

This review examined IOT-enabled electrical signature analysis for predictive maintenance of industrial motors, with particular attention to hybrid time-series approaches. Voltage, current, harmonics and phase imbalance can provide useful condition indicators, while IOT communication makes continuous monitoring and remote analysis possible. Prophet-style baseline forecasting and LSTM residual modelling offer complementary ways to identify departures from expected operation [1], [7], [8].

The source article reports promising results from a specific industrial monitoring case, but those findings should not be generalized without independent validation. Dependable implementation requires sound measurement practice, careful data management, transparent thresholds, cybersecurity, and maintenance-team review. The most useful predictive-maintenance system is not simply one that produces an anomaly score; it is one that provides credible evidence and helps staff make timely, justified maintenance decisions.



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