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IoT-Based Predictive Maintenance for AC Motors in Water Treatment Plants Using Multi-Sensor Data and LSTM Networks with GAN Augmentation

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Abstract

AC motors are critical assets in water treatment plants because they operate continuously to drive key processes. Reactive or schedule-based maintenance can miss early degradation and increase the risk of unplanned downtime. This study presents a field implementation of an Internet of Things (IoT)-based predictive maintenance system in a WTP. The system integrates vibration, temperature, and rotational speed (RPM) sensors with a cloud-based IoT pipeline for real-time data acquisition. Operational data were collected for 30 days from a single motor unit and analyzed using Random Forest and Long Short-Term Memory models. To address limited abnormal-event data, Generative Adversarial Network (GAN)-based augmentation was applied during training. The results show that LSTM performed more consistently than Random Forest; after augmentation, the F1-score improved from 0.92 to 0.95. The monitoring data also captured warning-level changes during operation, including vibration up to 3.9 mm/s, temperature up to 95 °C, and rotational speed dropping to around 1420 RPM, which may indicate abnormal operating conditions requiring inspection. Given the single-unit scope and short duration, the findings are reported as an initial implementation case study. Nevertheless, the work demonstrates the feasibility of a low-cost IoT-based monitoring and prediction framework to support maintenance decisions in WTP operations.

INTRODUCTION

Water treatment plants (WTPs) are expected to run continuously and deliver stable water quality despite changes in raw-water conditions and daily operational demands [1], [2]. In practice, the reliability of a WTP is also shaped by the reliability of its rotating equipment—especially AC motors that drive pumps, mixers, and agitators. When one of these motors starts to degrade, the impact is rarely limited to the motor itself: the disturbance can propagate into process interruptions, delayed treatment steps, and additional costs related to unplanned maintenance actions and production losses [3].

In many facilities, particularly the PT Semen Indonesia Gresik Plant WTP, motor maintenance is still performed after significant damage is discovered (reactive maintenance) or based on a fixed schedule (time-based preventive maintenance). Both approaches have drawbacks. Reactive maintenance risks detecting problems too late, while schedule-based maintenance does not always reflect the actual operating conditions of the motor. Motor damage can build up gradually—imbalance, bearing wear, misalignment, increased friction, or abnormal heating—and can be missed if inspections are not performed regularly or only occasionally [1], [4]. From an operational perspective, this mismatch creates two common outcomes: maintenance is performed too late (after the fact) or too early (without clear evidence), which is inefficient and can increase maintenance costs at the PT Semen Indonesia WTP.

Monitoring AC motor condition using a dashboard offers a more practical compromise. The dashboard monitors machine condition using vibration, temperature, and rotational speed (RPM) parameters. Data is sent in real time from various field conditions. Vibrations can reflect mechanical disturbances, temperatures can indicate friction between the iron and the pool's bottom rocks, and changes in RPM can reveal operational instability or AC motor drive problems [5]. Therefore, a monitoring system that consistently captures the signals sent by these IoT devices is useful, not only for reporting field trends, but as a sign or indication of AC motor machines that are starting to fail and need to be checked before they worsen.

The availability of low-cost Internet of Things (IoT) components has made continuous monitoring more feasible for many plants, including those that cannot justify high-end industrial systems for every asset. In the WTP context, IoT systems are widely reported for water-quality monitoring (e.g., pH, turbidity, dissolved oxygen, and temperature) and operational parameter logging [6], [7]. Several studies also show that microcontroller-based platforms can support flexible data acquisition at relatively low cost [3], [4]. However, a recurring limitation in many WTP-related IoT deployments is that the system stops at monitoring. Data are displayed and archived, but predictive analysis is not always integrated in a way that supports earlier maintenance decisions for critical mechanical assets [8].

Predictive maintenance (PdM) methods based on machine learning have shown encouraging results in other industrial domains. Models such as Random Forest (RF) are often used as strong baselines for multi-feature classification, while Long Short-Term Memory (LSTM) networks are frequently selected when the data are time-dependent and patterns unfold across sequences [9], [10], [11], [12]. Nevertheless, well-described field implementations that connect IoT-based multi-sensor monitoring to time-series machine learning for WTP motor assets are still limited, particularly for AC motors that operate continuously under real plant constraints (installation practicality, data quality variation, operational fluctuations, and maintenance workflow integration) [13], [8].

Another practical issue is the scarcity of failure examples. In real operations, abnormal events are not only undesirable but also infrequent, meaning that training data can be imbalanced and labels can be limited. Recent work has explored the use of Generative Adversarial Networks (GANs) to generate synthetic samples that resemble rare patterns, with the goal of improving model robustness under data scarcity [10], [14], [15]. Although this idea is increasingly discussed in predictive maintenance research, systematic reporting of GAN-assisted augmentation for WTP motor monitoring remains uncommon.

This study reports an implementation-oriented evaluation of an IoT-based predictive maintenance system for monitoring an AC motor in a WTP environment. The system integrates vibration, temperature, and RPM sensing using an embedded IoT device and a cloud-based data pipeline for real-time acquisition and storage. Operational data were collected for 30 days from a single motor unit in the field [“agitator motor 1 in the chemical mixing stage”], and predictive models were evaluated using RF and LSTM, with GAN-based augmentation used to address limited abnormal-event data. The work focuses on three questions: (1) whether a low-cost multi-sensor IoT setup is feasible and stable in an operating WTP, (2) whether the collected data support early indication of abnormal motor behavior, and (3) how model performance differs between RF and LSTM under the same field dataset, including the effect of data augmentation.

By focusing on a real deployment (rather than a purely simulated dataset), this study aims to provide practical insight for WTP technicians and managers who want to move from periodic inspection toward data-supported early warning. The results are presented as an initial implementation case study, with limitations clearly acknowledged, to support future scaling across multiple motor units and longer observation periods.

To clarify the position of this work, Table 1 summarizes related studies in IoT-enabled monitoring and data-driven maintenance. Most published work in the water sector emphasizes water-quality sensing and reporting, while fewer studies document field deployment for rotating equipment where vibration–temperature–RPM are analyzed together for early warnings.

Table 1. comparison with other studies

Authors	Challenges	Methods	Features
N. Mumtaz et al. [6]	- Data security-Interoperability-Scalability-Role of human operators	- IoT sensors-Data analytics-Automated systems-AI and ML	- Real-time monitoring-Data-driven decision making-Resource optimization-Enhanced safety
S. Das et al [15]	- Requires diverse expertise-Connecting multiple dots	- AI algorithms-IoT-enabled sensors	- Predictive analysis-Risk assessment-Timely decision-making
V. K. Sandhwar et al [7]	- Water scarcity-Pollution-Climate change	- IoT-Satellite-based remote sensing-Big Data analytics-AI	- Real-time data-Predictive insights-Proactive management
A. E. Alprol et al. [14]	- Data security-Scalability-Standardization	- IoT-based automated systems-Cloud computing-ML methods	- Real-time monitoring-Data analytics-Automation
A. Ishtaiwi et al. [16]	- Technological challenges-Socioeconomic challenges-Policy challenges	- Real-time sensor networks-ML algorithms-Automated irrigation control	- Water savings-Higher water use efficiency-Increased crop yield
C. Anitha et al. [17]	- Data security-Scalability-Standardization	- IoT sensor networks-Big Data analytics	- Real-time monitoring-Predictive analytics-Response mechanisms
T. Jomjaiekachorn et al. [7]	- Data security-Scalability-Standardization	- IoT sensors-Edge computing-ML models	- Real-time assessment-Predictive analysis-Data visualization
H. M. Forhad et al. [4]	- High costs-Technical complexities-Infrastructure alterations	- Advanced sensor technologies-Cloud-based storage-PLC-based control	- Real-time alerts-Historical data logging-Remote monitoring
T. Miller et al. [19]	- Data quality-Interoperability-Security-Technical constraints-Ethical concerns	- AI agents-IoT devices-Predictive modeling-Real-time analytics	- Enhanced data precision-Cost efficiency-Scalability
Y. K. Wang et al [10]	- Sensor reliability-Data management-System integration	- Smart sensors-IoT microcontroller-Cloud database	- Real-time monitoring-Data analytics-Visualization

As summarized in Table 1, the literature has widely discussed IoT–AI frameworks for water infrastructure, including security, scalability, and real-time analytics. In contrast, practical reports that connect multi-sensor motor condition data to predictive maintenance modeling in a WTP—particularly using time-series learning and strategies to handle limited abnormal data—are still limited. Therefore, this work focuses on a 30-day deployment on an agitator motor and evaluates RF and LSTM models, supported by GAN-based augmentation.

METHODS

Proposed Methodology

This study develops and evaluates an IoT-based monitoring system intended for predictive maintenance of a critical motor-driven asset in a Water Treatment Plant (WTP). The work is conducted as a field implementation study. The overall workflow covers: (1) designing and assembling the IoT sensing node, (2) collecting multi-sensor data from the target unit, (3) preparing the dataset through preprocessing and feature extraction, (4) training predictive models using the collected measurements, and (5) presenting the outputs in a dashboard so that technicians and supervisors can review trends and warnings. The complete research flow is illustrated in Figure 1.

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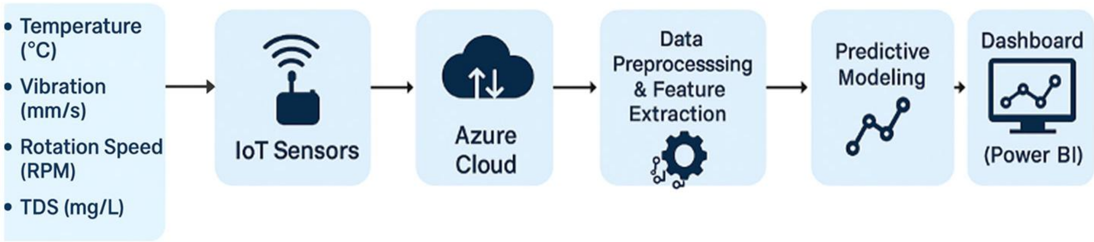

Figure 1. Research Metodology

The workflow adopted here follows common practice in IoT-based condition monitoring studies, where sensor measurements are streamed, prepared, analyzed, and then summarized into operationally readable outputs (e.g., trends and alerts) rather than being left as raw data logs [11], [4],[20].

IoT System Design

The IoT node was installed on one agitator unit at the WTP and integrates three sensors: vibration, temperature, and rotational speed (RPM). The vibrations were measured using an ADXL345 accelerometer sensor (±16 g). This sensor was selected because it is easy to integrate with embedded systems, has low power consumption, and is adequate for a prototype condition-monitoring setup. Temperature was measured using a DS18B20 sensor to observe motor/bearing temperature during operation. Rotational speed of the agitator is measured using an A3144 Hall effect sensor that detects the rotation of the shaft with the help of a small, attached permanent magnet.

An ESP32 microcontroller was used as the main controller for sensor reading and data transmission. Accelerometer sensors are mounted on the motor bearing housing to record dominant vibrations with a high degree of accuracy. The temperature sensor is placed as close as possible to the hottest point within the bearing or motor body to accurately represent thermal changes during operation. The RPM sensor is mounted near the shaft/magnet to maintain more stable detection. The sensor module and placement arrangement are shown in Figures 3 and 4.

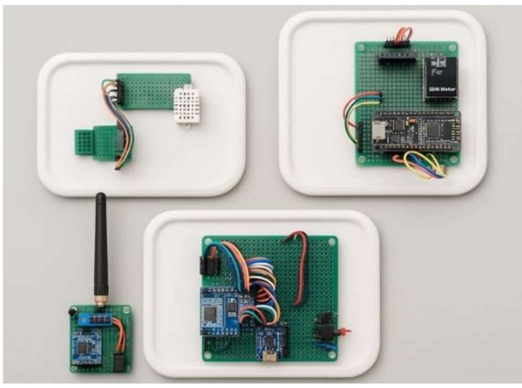

Figure 3.IoT Sensor

Figure 4. IoT sensor placement in water treatment

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The use of ESP32 and prototype-grade sensors is intentional in this study: the goal is to evaluate whether a relatively low-cost setup can function reliably for continuous monitoring in a WTP environment, as suggested in other IoT monitoring work in environmental and industrial contexts [21], [4]. The study site is a WTP with fluctuating raw-water characteristics (river water and rainwater-fed lakes), which provides realistic operational variability for testing the proposed system. The installation location is presented in Figure 5.

Figure 5. WTP research location

Data Acquisition

Data were collected from one agitator unit at a medium-scale WTP during the observation period. The recorded parameter were motor vibration, bearing/motor temperature, and shaft rotational speed (RPM). Vibration was sampled at the highest rate supported by the ADXL345 hardware configuration, up to 3.2 kHz. Accordingly, the initial "1–5 kHz" target stated during the design stage was implemented in practice within the maximum achievable range of the sensor. This sampling rate was selected to capture vibration components that are relevant for a medium-speed motor while still matching the limits of the prototype hardware.

Temperature was recorded at 1 Hz. RPM was recorded at a lower rate, which is sufficient because RPM does not typically change as rapidly as vibration. Measurements were transmitted over Wi Fi using MQTT. Each message was packaged in JSON format and included (at minimum) a timestamp, sensor identifier, and measurement value, so the dataset could be traced and checked consistently during storage and analysis. This acquisition pattern is consistent with common IoT practices used in water and environmental monitoring deployments [4], [21].

Data Preprocessing and Feature Extraction

Field sensor streams are rarely perfect. In our recordings, the raw data contained measurement noise, occasional missing samples, and sporadic spikes that could distort the learning process if used directly. For that reason, preprocessing was applied before feature computation.

Vibration was sampled up to 3.2 kHz using the ADXL345. A fourth- order Butterworth low pass filter with a cutoff frequency of 1000 Hz was then applied to the vibration signal to attenuate high frequency content that is not associated with the mechanical condition targeted in this study. Missing values were handled based on gap duration: short gaps were filled using linear interpolation, while longer gaps were completed using simple statistical imputation based on nearby observations.

Outliers were removed using a two stage procedure. First, we performed Z score screening with a threshold of $|Z| > 3$. Second, a Hampel filter with a window size of 11 samples was used to suppress remaining spikes while preserving local trends in the signal [12]. After cleaning, features were computed per window. Feature vectors were computed using non-overlapping 1-second windows (3200 samples per window at 3.2 kHz). Time domain features include RMS, variance, kurtosis, and crest factor, which summarize the overall vibration level and impulsive behavior. In addition, fixed indicators at the PT Semen Indonesia WTP operational unit are included, such as the rate of temperature change and the RPM movement size. This combination of pre-processing and multi-sensor features follows common practices in sensor-based predictive maintenance studies [10], [22].

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Predictive Modeling Procedure

Researchers used two modeling approaches to test the results and differences between the two models: Random Forest (RF) and Long Short Term Memory (LSTM). RF was used as a baseline because it performs reliably with multivariate feature sets and provides a stable reference for normal vs. abnormal classification. LSTM was selected because the plant measurements evolve over time; the model can learn temporal patterns across vibration, temperature, and RPM signals.

For sequence modeling, the LSTM input consisted of sequences of length L=60 consecutive feature windows. With 1 s non overlapping windows, each sequence represents 60 s of operation. This design allows the model to use recent history rather than relying on a single time point. Because real abnormal/failure events are limited in the field dataset, GAN based data augmentation was used during training to reduce class imbalance. The GAN was trained to generate synthetic samples that resemble rare anomaly patterns, and the generated samples were added only to the training set to improve robustness, as suggested in data driven predictive maintenance research [11]. Figure 6 depicts the LSTM based WGAN architecture used in this study.

To avoid data loss- the processed dataset was split chronologically: the first 70% of observations (approximately the first 21 days) were used for training, and the remaining 30% (approximately the last 9 days) were reserved for further testing. Model performance was evaluated using accuracy, precision, recall, and F1 score. The validation selection followed the practice of time series evaluation, where preserving the time sequence helps prevent overly optimistic results caused by data leakage [9].

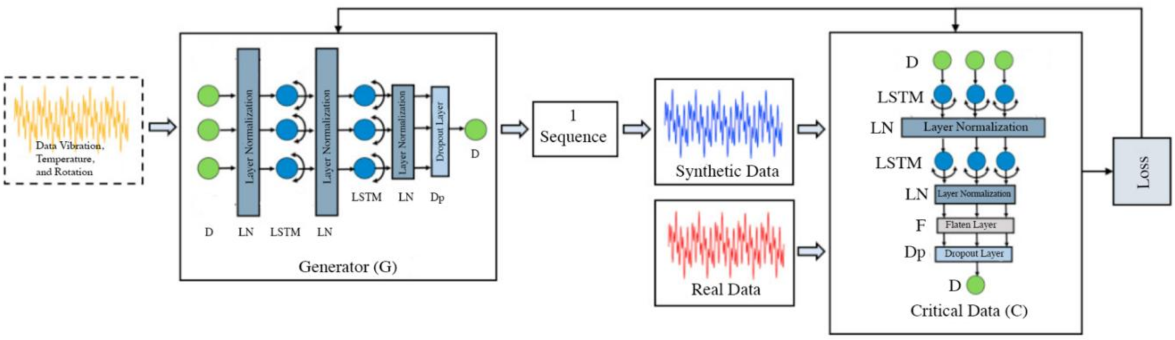

Figure 6. Proposed LSTM Networks with GAN Augmentation

This research utilizes multi-sensor data, including temperature, vibration, and rotational speed (RPM), which are arranged as a time series. Each sample is formed within a window of length L so that the model receives a sequence of inputs.

$$X_t = [T_t + V_t + R_t] \text{ .... (1)}$$

For classifying motor conditions (e.g., normal and abnormal), an LSTM network is used to process the sensor sequence and generate the final state. X_t , Then, the data is mapped into class probabilities using the specified function *softmax*

$$\check{y} = softmax(Wh_l + b) \text{ .... (2)}$$

The LSTM parameters are optimized using cross-entropy loss so that the class predictions are close to the actual labels. To increase the variety and amount of training data, especially when anomalous data is limited, a WGAN-augmented GAN is used, which generates synthetic sequence data that resembles the patterns of the original data.

$$\mathcal{L}_D = E\,[D(\check{X})] - E[D(X) + \lambda E(\|\nabla_{\check{X}} D(\check{X})||_2 - 1)^2 \text{ .... (3)}$$

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The synthetic data was then combined with real data to create a new dataset D_{Train} to train the LSTM [9], so that the model is expected to be more adaptive in recognizing anomaly patterns in WTP operating conditions.

Visualization and Decision Support

To make monitoring results usable in day-to-day operations, the output from the analysis and prediction phase is displayed in an interactive dashboard. The dashboard- shows time trends of key sensor readings (vibration, temperature, and RPM), health indicators of powered-on AC motors, and alert notifications when the system detects deviant or unusual behavior (Figure 7). The application's dashboard allows users to easily see what's happening to the machine and track changes in condition in real time. The dashboard is intended for two user groups. For technicians, it provides detailed time-series plots and status information to support field inspections. For supervisors and WTP managers, it helps summarize key indicators and alert statuses so that maintenance actions can be planned in advance, including scheduling inspections and allocating resources based on recorded evidence [23], [8].

Our sensor research aligns with the development of other IoT applications, which utilize intensive data recording to monitor machine condition [4], Data is managed using an automated Azure system. We employ a single-flow (Kappa) method to ensure continuous data flow and maintain system performance even as data volumes increase [11]. To obtain optimal results, predictive models (Random Forest and LSTM) are applied to the collected signals [10]. Model evaluation is performed chronologically to avoid prediction errors due to random mixing of time data [9]. and finally, the results are presented in a Power BI dashboard so that technicians and supervisors can access the same evidence in an easily accessible information [25], [26], [19].

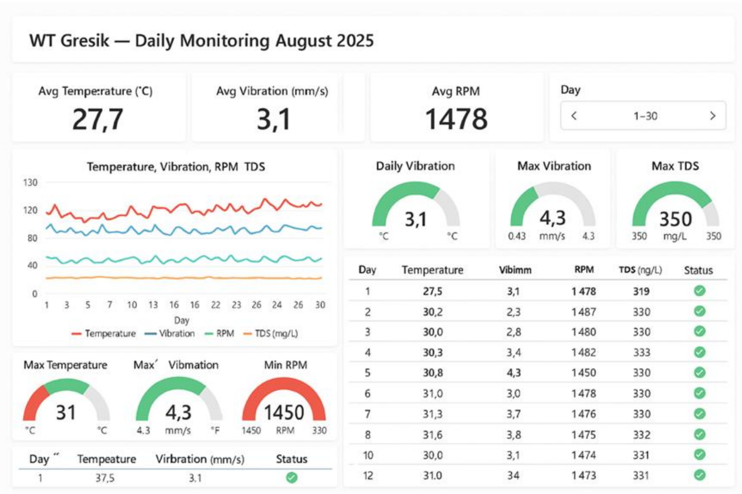

Figure 7. Power BI dashboard water treatment

Method Limitations

This study has several limitations. First, the evaluation was carried out on only one equipment unit and over a relatively short observation period. Second, the sensing hardware used was prototype-grade, so its measurement resolution and long-term stability may be lower than those of industrial condition-monitoring sensors. For these reasons, the results should be read as an initial field implementation that examines practicality and early potential of an IoT-based predictive maintenance approach in a real WTP environment, not as a full long-term reliability verification of an industrial-scale system.

RESULTS AND DISCUSSION

Experimental Results

The experimental results show that combining vibration, temperature, and RPM measurements through the proposed IoT setup makes it possible to observe early shifts in the operating pattern of the monitored AC motor. Across the 30-day observation period, changes in vibration appeared earlier than the rise in temperature and the later RPM variation, suggesting that vibration is the most sensitive

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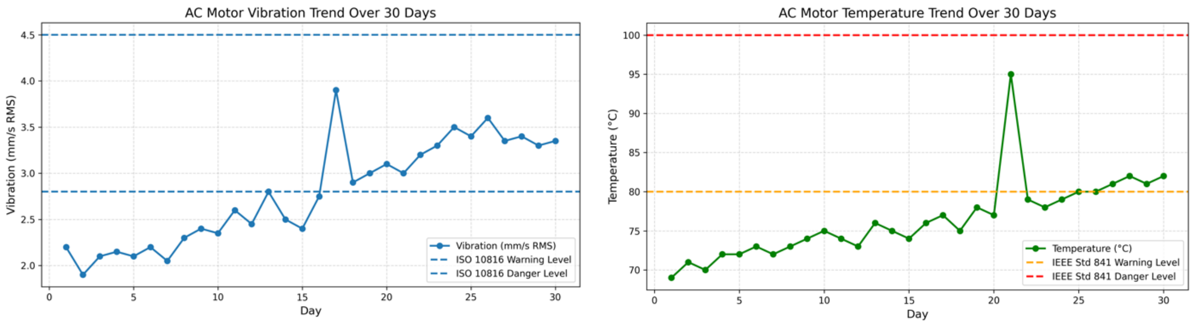
indicator for the initial stage of mechanical degradation in this case. This observation is consistent with commonly used vibration severity guidance (ISO 10816 standards) , where an increase in vibration level is often one of the earliest signs of developing bearing or mechanical issues [2], [19] . In our data, the warning range of 2.8–4.5 mm/s corresponds to the first indication of deterioration and is illustrated in Figure 8.



a b

Figure 8. Trends AC Electric Motor Vibration (a) & AC Electric Motor Temperature (b)

Figure 8 also shows the temperature trend of the motor during operation. The average temperature during the monitoring period was around 72 °C, with a sharp increase reaching 95 °C on day 21 (Figure 8b). This value falls within the warning band reported in IEEE Std 841 (80–100 °C), which may indicate overheating related to increased load, friction, or other abnormal operating conditions [1], [27].

To further inspect the signal behavior over time, a time–frequency analysis was conducted using spectrograms (Figure 9). The spectrograms indicate that the augmented vibration data produced by the WGAN preserves key characteristics of the real signal. In particular, the dominant frequency components and their relative intensity patterns remain similar between the synthetic and observed data after training, which supports the use of augmentation to enrich rare-pattern examples in the dataset.

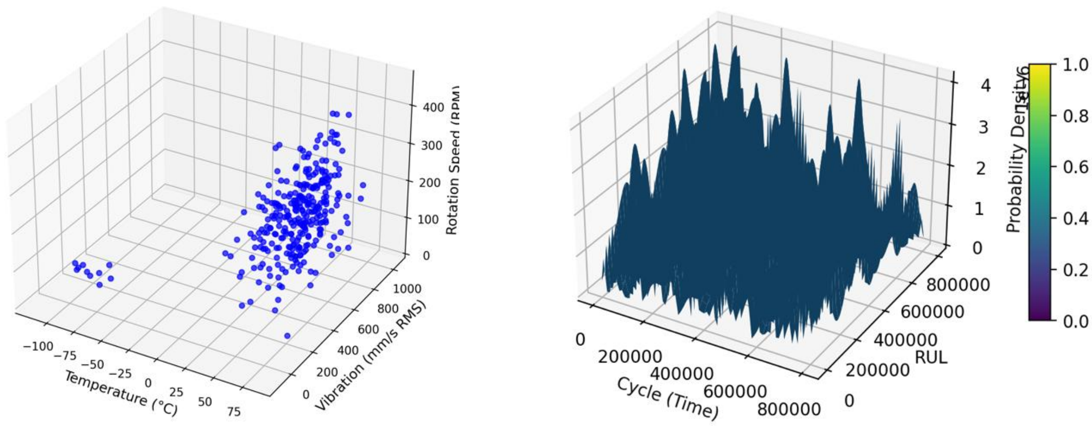


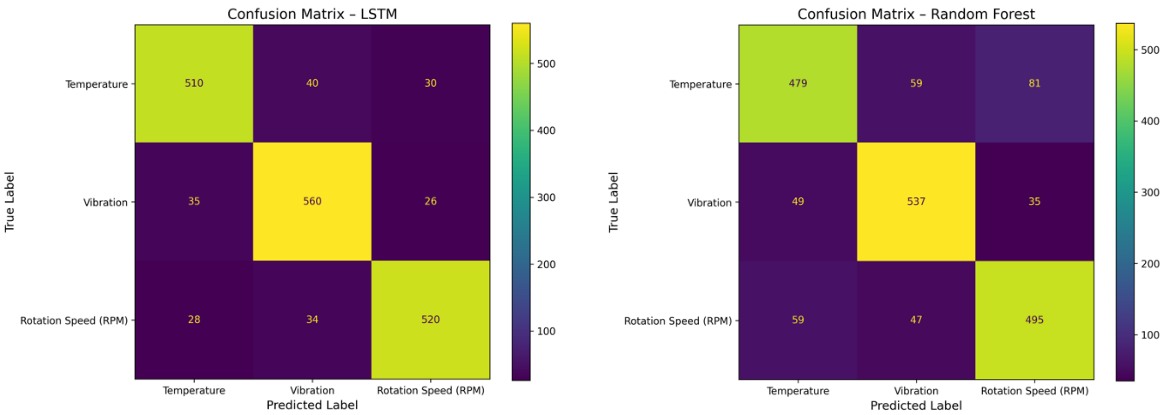
Figure 9. Spectrogram analysis for observed temperature, vibration and rotation

The developed IoT-based predictive maintenance system was deployed successfully on an AC motor drive in the WTP. Over 30 days, the system collected approximately 837,000 sensor records, including vibration, temperature, and RPM data points transmitted in real time. The dataset was then processed and used to train two models—Random Forest and LSTM—and the overall performance comparison is summarized in Table 2.

Table 2. Model Performance Comparison

Model	Accuracy	Precision	Recall	F1-Score
Random Forest	0.93	0.91	0.90	0.90
LSTM	0.95	0.94	0.92	0.93

Both models achieved strong classification performance for separating normal and abnormal conditions, with accuracy above 90% in the main evaluation. Random Forest reached an accuracy of 0.93 with precision 0.91, recall 0.90, and F1-score 0.90. LSTM produced consistently higher scores, with accuracy 0.95, precision 0.94, recall 0.92, and F1-score 0.93 (Table 2). These results suggest that, on this dataset, LSTM benefits from modeling the sequential nature of the sensor features and can better capture how abnormal patterns develop over time.



a b

Figure 10. Model test accuracy comparison LSTM (a) & Random Forest (b)

Figure 10 provides an additional view of model behavior during testing. In the Random Forest result shown there, the model achieved an accuracy of 0.8034, while precision (0.1093) and recall (0.2407) were much lower. This pattern typically reflects the impact of class imbalance: abnormal events are rare, so a model can appear "accurate" overall while still missing many abnormal cases or producing unstable precision/recall for the minority class.

Operationally, the ability to detect defects is crucial. Missing a single defect is far more costly than addressing multiple false alarms. Our results show that the LSTM model excels at detecting abnormal conditions (high detection rate), as evidenced by its recall of 0.92 and accuracy of 0.95. This advantage is beneficial for early warning systems, although it may require additional tuning to reduce false alarms. Therefore, model selection should consider the real-world impact: which is more detrimental, missing problems or generating too many false alarms, rather than simply pursuing statistical accuracy alone.

Anomaly Detection Analysis Results

To detect anomalies without labeled data, researchers used the Isolation Forest and Autoencoder methods. These techniques identify pattern deviations in combined sensor data (temperature, vibration, and RPM). The analysis results are shown in Tables 3 and 4.

Table 3. Isolation Forest Results

No	Date & Time	Temperature (°C)	Vibration	RPM	Anomaly Score
1	2025-09-14 10:40	31.94	339	60.00	**-0.246616**
2	2025-09-14 10:40	31.94	317	60.00	-0.245930
3	2025-09-14 10:40	32.00	291	60.00	-0.245531
4	2025-09-14 10:40	31.94	281	60.00	-0.244825
5	2025-09-14 10:40	31.94	280	**2.61**	-0.244825
6	2025-09-14 10:40	31.94	285	60.00	-0.244785
7	2025-09-14 10:40	31.94	130	60.00	-0.242875
8	2025-09-14 10:40	31.94	265	60.00	-0.242625
9	2025-09-14 10:40	31.94	265	60.00	-0.242625
10	2025-09-14 10:40	31.94	271	60.00	-0.241153

Table 3 lists ten extreme anomalies reported by Isolation Forest model. The highlighted points were gathered at one time only (September 14, 2025 at 10:40), so it is not random noise, but rather a brief disturbance that occurred at that time. The anomaly was primarily caused by unusually high vibration readings (many values above 300) while the RPM remained near 60. One record shows a sudden drop in RPM to 2.61, which is inconsistent with the surrounding points and may indicate a brief operational interruption or measurement/sensor issue. The temperature values remained relatively stable at the same time, indicating that the anomaly pattern was dominated by the vibration-RPM combination rather than a thermal event in the AC motor at the WTP.

The table analysis indicates that Isolation Forest can capture these brief, anomalous moments—those that are often easily missed when looking at long time-series logs. In maintenance practice, these signs could indicate a momentary mechanical disturbance (e.g., slight misalignment, looseness), but could also be due to a sensor issue. In essence, the model will flag those points as "unusual" because the combined pattern of all variables looks aberrant, not just because one variable crosses a fixed threshold.

Table 4. Most extreme anomalies for the autoencoder method

Date & Time	Temperature (°C)	Vibration	rpm	recon_error
2025-09-11 18:54	58.0	224	391	33.918
2025-09-14 06:17	58.0	316	328	23.822
2025-09-15 03:54	58.0	255	304	20.481
2025-09-14 10:40	31.94	0	60	944
2025-09-14 10:40	31.94	10	60	943

Autoencoder data: Table 4 shows the most extreme data according to the calculation results. Compared to Isolation Forest, the autoencoder flags "anomalous" data because the combined pattern of values is not as predictable as normal conditions. The most severe case occurred on September 14, 2025, at 10:40 AM: where the temperature was 31.94, vibration was zero (or nearly zero), and the RPM was 60, with a recon error of 944. This is highly suspicious because it is likely due to a sensor problem (e.g., a loose sensor, a saturated signal, or a data drop), rather than the AC motor itself.

Of the 802,390 training data points obtained at WTP, approximately 5% (40,119 points) were detected as anomalies based on the reconstruction error threshold. Most anomalies occur when the combination of values is unusual—for example, extremely high temperature, abnormal RPM, or extreme/suddenly zero vibration. Because it does not require a fault label, the autoencoder is suitable for simple fault cases and can capture fairly complex patterns.

Table 5. Comparison of Isolation Forest vs. Autoencoder on WTP

Model	AUCPR	False Alarm Rate
Isolation Forest	High (stable)	Lower
Autoencoder	More sensitive	Slightly higher

Table 5 summarizes the differences in anomaly detection model used in this study. Both model can be used, but they emphasize different considerations. Isolation Forest tends to be simpler and computationally lighter, and can provide stable anomaly flags suitable for rapid filtering in near-real-time applications. Autoencoders are more sensitive to complex and rare variable combinations, which can be beneficial for more in-depth analysis of WTP conditions.

Therefore, the choice of model should depend on the monitoring objectives. If the priority is fast detection with low computational overhead for routine operational monitoring, Isolation Forest is a practical choice. If the priority is capturing more subtle or non-linear anomaly patterns for research analysis or for a more sensitive early warning layer, autoencoders are more attractive. Based on the results of this study, Isolation Forest is more recommended for implementation in the PT Semen Indonesia WTP IoT.

Discussion of Results

The implementation of the model at PT Semen Indonesia's WTP (Water Treatment Plant) demonstrated that the system can provide notification if the AC motor is in an abnormal condition. Three important factors influence this:

First, vibration typically increases before other indicators. During monitoring, the increase in vibration was observed before the temperature spiked and before the RPM dropped. This makes sense because early signs of mechanical problems—especially bearing-related—often arise from vibration.

Second, the IoT flow (sensor–send data–storage–dashboard) supports WTP operations. Operators no longer need to wait for periodic checks; they can simply observe trends and warning signs or notifications to determine when manual inspections are necessary. This allows maintenance to be performed sooner, rather than after damage has occurred.

Third, the temperature rose to 95°C during higher pump loads. This indicates that temperature is related to operating load. This finding aligns with Arivalagan and Srinivasan [28], who explain that temperature and other operational conditions are more accurate indicators of machine failure. Findings at the WTP indicate that frequent overheating can accelerate insulation aging and increase the risk of machine failure.

Significance Findings

This work provides two main contributions at the implementation level.

Feasibility of a low-cost field deployment. The study demonstrates that an ESP32-based multi-sensor node (vibration, temperature, and RPM) can be installed and operated in a WTP environment and can produce a usable dataset for analysis and monitoring. This is a practical result: it shows that continuous data collection for motor condition monitoring is achievable without relying on high-end industrial monitoring systems.

Value of multi-sensor monitoring for early warning. Using vibration, temperature, and RPM together provides a more complete picture than relying on one signal only. In the dataset, abnormal patterns were clearer when the variables were interpreted jointly, which is consistent with existing literature on condition monitoring and predictive maintenance [26].

Regarding the operational benefit claim (e.g., reduced unplanned downtime), the result in this study should be treated as a potential outcome rather than a verified impact. The study did not include a long-term controlled comparison or formal statistical evaluation of downtime reduction. Therefore, the statement about up to 25% reduction is best framed as a target/KPI reference or an indicative expectation, not as a proven quantified benefit. The main value of the present work is that it establishes a working prototype and a field dataset that can support a stronger evaluation in future trials.

CONCLUSION

This study investigated an IoT-based predictive maintenance system for monitoring AC motors. Data was collected over 30 days from a single motor. During the monitoring, significant changes were observed: vibration reached 3.9 mm/s, temperature rose to 95°C, and rotation dropped to around 1420 RPM. These analysis results are outside the normal range and can therefore be considered warning signs of impending failure. However, this does not necessarily indicate actual motor failure—rather, the data indicates unusual behavior that requires further investigation in the field.

Several methods were tested on this multi-sensor data: Random Forest and LSTM (supervised models), and Isolation Forest and autoencoder (unsupervised models). All were able to identify unusual patterns, but each model had a different alarming style—some were more sensitive, others more stable. While some metrics improved, the study did not use statistical tests to confirm the differences were truly significant. Therefore, the results are best read as an initial evaluation in a case study, rather than a test of whether one method is superior.

Combining vibration, temperature, and RPM sensor data has proven more useful than using a single parameter. This system has the potential to be an early warning tool at PT Semen Indonesia's WTP to support maintenance decisions. However, claims such as cost savings, reduced downtime, or increased reliability are uncertain because it has not been tested long-term.

The study's limitations are clear: this study only monitored one AC motor for a relatively short period of time, the sensors used at the WTP are still prototypes, and more detailed diagnostic analysis (e.g., vibration frequency analysis for specific types of damage) has not been fully discussed. Operational aspects such as alarm response standard operating procedures (SOPs), technician training, integration into maintenance workflows, and cost analysis have not been addressed.

In the future, the study should be expanded to a longer period and include more sensors installed on more AC motors, with more robust statistical evaluation. Furthermore, the study could include frequency analysis, RUL estimation, and edge computing options. From an operational perspective, alarm handling regulations are needed to prevent false alarm notifications, as well as integration into the maintenance management system for daily use at PT Semen Indonesia's WTP.

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