# Predictive Maintenance and Monitoring of Industrial Compressors Using Machine Learning: A Proactive Approach

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**Abstract:** In the era of Industry 4.0, predictive maintenance has become a cornerstone for ensuring operational efficiency, minimizing downtime, and extending the lifespan of industrial equipment. This paper presents a comprehensive approach to predictive maintenance and real-time monitoring of industrial air compressors using machine learning techniques integrated with Internet of Things (IoT) infrastructure. The proposed framework leverages a multi-sensor setup to continuously collect critical parameters such as temperature, pressure, and flow rate from compressor units. These data streams are transmitted to a cloud-based Structured Query Language (SQL) database, enabling centralized and scalable storage for real-time analytics. A Linear Regression algorithm was trained on historical sensor data to detect performance anomalies and forecast potential failures. The optimized model was then deployed for real-time inference. When monitored parameters exceeded pre-set thresholds, the system autonomously triggered alerts through email notifications, allowing timely intervention and preventive action. The machine learning model demonstrated high reliability, achieving a prediction accuracy of 98% as measured by the Mean Squared Error (MSE) metric. The integration of IoT and machine learning facilitates proactive maintenance strategies, reducing the risk of unexpected equipment failure and enabling continuous condition monitoring without manual intervention. The findings underscore the potential of intelligent maintenance systems to drive significant improvements in asset management, cost efficiency, and operational safety across industrial settings.

Keywords: Predictive Maintenance; Machine Learning; Industrial Compressors; IoT Monitoring; Data Acquisition; SQL Database; Linear Regression; Fault Prediction; Real-Time Analytics; Condition-Based Maintenance.

## 1. Introduction

The industrial sector is undergoing a rapid transformation driven by digitalization and automation. Among the critical advancements shaping this new industrial paradigm is predictive maintenance (PdM)—an approach that utilizes historical and real-time data to predict equipment failures before they occur. Unlike traditional preventive or corrective maintenance, predictive maintenance optimizes repair schedules, ensuring equipment is serviced only when necessary. This reduces operational downtime, extends machine life, and lowers maintenance costs. The rise of Industry 4.0 has accelerated the adoption of smart technologies such as the Internet of Things (IoT), cloud computing, big data analytics, and artificial intelligence (AI), particularly in maintenance and reliability engineering. As industrial systems become more complex and interconnected, maintaining their operational efficiency has become increasingly data-dependent. IoT-enabled sensors now continuously collect machine condition data, which is processed using advanced analytics and machine learning algorithms to forecast potential failures. In the evolving landscape of industrial operations, predictive maintenance is proving to be a game-changer, offering a strategic pathway to boost operational reliability and efficiency [1] [2]. Rather than relying on traditional reactive maintenance, this approach proactively forecasts equipment failures and optimizes maintenance routines—thereby minimizing unexpected downtimes and extending the service life of machinery. Predictive maintenance typically follows two principal models: data-driven and experience-based methods, as depicted in Figure 1. These methods are increasingly enhanced by the synergy of Internet of Things (IoT) technologies and machine learning (ML) algorithms, enabling a dynamic system for real-time condition monitoring and fault prediction [3]. With the growing adoption of IoT, industries are now able to gather massive volumes of data from interconnected devices, establishing a solid framework for predictive analytics and system diagnostics. Concurrent advances in machine learning offer robust capabilities to interpret and model complex data patterns, delivering insights and predictions that were once beyond reach. Together, these technologies have catalyzed a significant shift—from reactive to intelligent, data-informed maintenance strategies—based on continuous data streams and real-time processing [3][4].

Despite these advancements, the full-scale implementation of predictive maintenance still faces notable hurdles, especially in managing and analyzing the vast datasets generated by industrial systems . Moreover, effective data handling, integration with legacy systems, and the interpretability of AI models remain critical concerns for widespread adoption. Industrial machines—especially compressors—are vulnerable to wear and failure due to extended usage and exposure to challenging operating environments. Common issues include moisture ingress, chemical exposure, overheating, and pressure or temperature fluctuations [5]. Over time, these stressors lead to material degradation, corrosion, and structural cracks, potentially causing performance drops and severe breakdowns [6]. To prevent such failures, temporal condition monitoring plays a pivotal role in predictive maintenance. Techniques like acoustic sensing, hyperspectral imaging, and laser scanning are widely used in various industries—including renewable energy sectors such as wind turbines to detect early signs of mechanical anomalies. The deployment of real-time, automated Non-Destructive Testing (NDT) further supports fault detection, helping reduce maintenance costs and prolong the durability and integrity of equipment [7] [8]. This study explores how advanced data acquisition systems and machine learning can be effectively combined in a real-world industrial setting to enhance the predictive maintenance of compressors. A practical case study conducted at Cégep de Sept-Îles is presented, where a comprehensive sensor network and the Ewon Flexy 205 module (developed by HMS Networks, Sweden) were installed to facilitate intelligent data collection and analysis. The innovation of this research lies in its holistic integration of IoT infrastructure, cloud computing, SQL databases, and AI algorithms—delivering a smart, scalable solution for compressor monitoring that hasn’t been explored in this depth before. Beyond theoretical modeling, this work demonstrates practical relevance for small and mid-sized industries by offering a highly automated and user-friendly system that minimizes manual intervention and error [8] [9] [10].

## 2. Literature Review

The integration of the Internet of Things (IoT) has become a game-changer in industrial environments, fundamentally altering how data is collected, interpreted, and acted upon. As per Kumar et al. (2024), IoT-driven platforms now support heterogeneous sensor networks that monitor temperature, vibration, acoustic emissions, and thermal conditions across different machinery. The data collected in real time creates a feedback loop enabling dynamic system optimization and condition-based maintenance [11]. According to Patel & Ghosh (2025), Industry 5.0 emphasizes personalized and resilient industrial automation, in which IoT plays a foundational role by enabling human-machine collaboration and remote diagnostics [12].

Singh et al. (2024) discuss how cloud-enabled IoT infrastructures facilitate not only local data processing through edge devices but also cloud-side analytics for deeper insight generation [13]. While this creates a robust operational ecosystem, Zhou et al. (2025) caution that real-time data acquisition via IoT also brings forth challenges like latency issues, bandwidth limitations, and data heterogeneity [14]. Moreover, Agarwal and Mehta (2024) argue for the necessity of encryption protocols and zero-trust architecture in securing IoT-based industrial environments against data breaches and ransomware attacks [15].

Mohamed et al. (2025) propose a hybrid model combining CNNs and LSTMs for compressor anomaly detection, showing superior performance in early failure prediction [16]. The study by Venkatesh and Roy (2024) also emphasizes the importance of low-latency inferencing through edge deployment of lightweight models like MobileNetV3 and TinyML frameworks, making real-time predictions feasible even in bandwidth-constrained environments [17].

The review by Das et al. (2025) explores the balance between predictive accuracy and computational complexity, noting that while transformer-based models outperform RNNs in multi-sensor environments, they require extensive tuning and GPU acceleration, which may not be practical for all industrial settings [18].

High-quality data underpins the accuracy of predictive models. According to Rajput et al. (2024), preprocessing techniques such as principal component analysis (PCA), wavelet transformation, and Kalman smoothing have proven effective in removing sensor noise and enhancing the signal-to-noise ratio in real-time industrial monitoring systems [19]

Elhadi et al. (2025) emphasize that data fusion from multiple sensor modalities—thermal imaging, ultrasound, and vibration analysis—significantly enhances model robustness. Their study demonstrates that fused data not only improves fault localization but also reduces false positives by up to 30%, making predictive systems more reliable [20].

## 3. Methodology

This section elaborates on the comprehensive methodology employed in the development of a predictive maintenance system for industrial compressors. It is structured into two major segments: the first detailing the processes involved in data collection and preparation, and the second focusing on the machine learning model implementation and evaluation metrics. The overall methodology, which illustrates the interplay between sensor systems, data acquisition tools, and machine learning models.

### 3.1 Data Collection and Preparation

The research was conducted at Cégep de Sept-Îles, where an industrial compressor unit was utilized as a testbed. To enable real-time operational monitoring, an advanced sensor suite was deployed. This suite comprised high-precision sensors such as Resistance Temperature Detectors (RTDs), current transformers, and pressure transmitters. These sensors were crucial for collecting critical operational parameters, which are essential for understanding the health and performance of the compressor. The sensor suite was integrated with a Siemens SIMATIC S7-1200 PLC (Programmable Logic Controller). This device, known for its reliability in industrial automation, was used to perform initial data collection and preprocessing. However, as the S7-1200 was primarily designed for control tasks, its capacity for extensive data analysis and storage was limited. To overcome this limitation, a Python-based script was initially developed to pull data from the PLC. Despite being functional, this solution was dependent on constant connectivity and was susceptible to data losses during connectivity failures [21] [22].

### 3.2 System Enhancement with Ewon Flexy 205 Module

To significantly improve data reliability and independence from manual connectivity, the setup was enhanced with the addition of an Ewon Flexy 205 industrial gateway. This gateway, which supports multiple industrial communication protocols, enabled autonomous real-time data acquisition and transmission to a cloud-based server. It provided several advantages: Data buffering during outages to prevent data loss, Encryption support to secure cloud transmissions, Flexible integration with diverse industrial networks. This upgrade ensured a robust, secure, and continuous flow of data, which is vital for deploying reliable predictive maintenance models. The stored data included time-stamped readings of various sensor outputs such as temperature, pressure, and electrical current. This structured data repository facilitated rapid access to historical data, which is a key requirement for developing, training, and validating machine learning models in predictive analytics.

### 3.3 Data Preprocessing and Feature Engineering

Before feeding the data into predictive models, it underwent several preprocessing steps to improve its quality and relevance. These steps included: Outlier detection and removal to enhance data consistency, Normalization of variables to ensure comparability, Handling missing values using interpolation and statistical methods, Feature engineering, which involved generating new variables from existing ones to better capture equipment behavior (e.g., temperature change rate, power consumption variance).These procedures ensured the creation of a clean, high-quality dataset suitable for accurate predictive modeling. The system comprises a Temperature Probe (RTD PT100) with a range of -200°C to +200°C for precise thermal monitoring, a Current Transformer (CCT50-200) supporting up to 200 Amps with a 4–20 mA output for current load detection, Pressure Transmitters (SITRANS P200) in 100 PSI and 300 PSI models for accurate pressure monitoring, Analog Input Modules (SIMATIC S7-1200 SM1231 AI and SM1231 AI RTD) for integrating analog and RTD signals with the PLC, and a Power Supply (SITOP PSU100L 6EP1333-1LB00) providing a stable 24VDC output from a 120/230VAC input to ensure reliable power delivery to all components [22] [23] [24].

Table 1. Instrumentation Summary Table [24] [25] [26]

| Sensor Concept | Model | Operating Range | Function | Method Consolidation |
|---|---|---|---|---|
| Temperature Sensor | RTD PT100, Munich, Germany | –200 to +200 °C | Monitors the temperature of the compressor and related fluids to detect overheating and evaluate thermal performance. | Connected to Siemens S7-1200 CPU |
| Current Sensor | CCT50-200 | 100/150/200 A, 4–20 mA Output | Tracks electrical current to evaluate load levels and identify irregularities that might suggest mechanical or electrical malfunctions. | Connected to Siemens S7-1200 CPU |
| High-Pressure Sensor | SITRANS P200 (7MF1565-4CD00-5FA1) | 0–300 PSI (relative) | Measures high-pressure conditions within the compressor unit to support safe and efficient operation. | Connected to Siemens S7-1200 CPU |
| Low-Pressure Sensor | SITRANS P200 (7MF1565-4BG00-5FA1) | 0–100 PSI (relative) | Measures lower pressure values, aiding in the monitoring of non-critical zones that still require accurate readings. | Connected to Siemens S7-1200 CPU |
| Analog Input Expansion | SIMATIC S7-1200 SM1231 AI | 13 Bit ± 10VCC / 0–20 mA | Enhances the CPU's input range, allowing it to process signals from a variety of sensors with different measurement characteristics. | Connected to Siemens S7-1200 CPU |
| RTD Input Expansion | SIMATIC S7–1200 SM1231 AI RTD | 16 Bit RTD (compatible with various RTDs) | Optimized for precise temperature readings from RTD sensors, supporting temperature-sensitive monitoring operations. | Connected to Siemens S7-1200 CPU |
| Power Supply Unit | SITOP PSU100L 6EP1333-1LB00 | 24VDC, 5A (input: 120/230VAC) | Delivers consistent and secure power to all connected sensors and the PLC, ensuring stable system performance. | Connected to Siemens S7-1200 CPU |

The equipment table is well-organized with clear categorization of sensor types, enhancing readability. Model specifications are well-detailed, but including datasheet references or links would improve traceability. While measurement ranges are thorough, mentioning sensor accuracy or tolerance would add technical depth. The function descriptions are clear and practical, though tying each to its role in the machine learning workflow (e.g., feature extraction or anomaly detection) would reinforce relevance. Integration details are consistent, but specifying communication protocols like Modbus or Profinet could provide more clarity. The inclusion of the power supply unit shows completeness; however, noting any backup systems would be beneficial. Lastly, indicating how each sensor supports predictive analytics would align the table more closely with the machine learning-based maintenance approach. The entire data acquisition system, built around the Siemens S7-1200 PLC, aggregates, preprocesses, and transmits data to the cloud using the Ewon Flexy 205 module. SQL databases facilitate the structured storage of this data, enabling seamless integration with the machine learning models used for predictive maintenance. This end-to-end system architecture ensures a scalable, secure, and reliable solution for monitoring and maintaining industrial compressor systems. This study utilizes data collected from an industrial air compressor system located at Cégep de Sept-Îles. The system is instrumented with a comprehensive suite of sensors, including temperature sensors, pressure transmitters, and current transformers, which continuously record operational parameters in real time. The collected dataset includes temperature (°C) from key compressor locations such as intercoolers and motor assemblies, pressure (PSI) across various compression stages, and electrical current (A) from all power phases, with each reading timestamped to create time-series data suitable for predictive analysis; data acquisition was performed using the Ewon Flexy 205 industrial gateway, which transmitted readings to an SQL database for structured storage, and preprocessing involved missing data imputation using mean values, outlier detection and removal through statistical methods, and normalization using StandardScaler to standardize input variables for machine learning models [26] [27] [28].

Parameter Tuning and Model Selection: In this study, Linear Regression was chosen for predictive maintenance due to its balance of efficiency, transparency, and proven performance in estimating continuous variables from industrial sensor data, with its low computational cost enabling real-time deployment, its interpretability aiding in maintenance decision-making, and its suitability for regression-based tasks—notably aligning with the continuous nature of data like temperature, pressure, and electrical current—while hyperparameter tuning and model configuration were optimized to integrate these diverse sensor inputs into a unified, proactive monitoring framework.

Model Evaluation: After data preprocessing, the Linear Regression model was trained on the multivariate dataset using cross-validation techniques to enhance reliability. The model's accuracy was evaluated using the Mean Squared Error (MSE) metric, which quantifies the average squared difference between predicted and actual values. The performance of the predictive model was evaluated using the Mean Squared Error (MSE) metric, as shown in Equation (1). MSE calculates the average of the squared differences between predicted values (xi) and actual values (yi), providing a quantitative measure of prediction accuracy. Lower MSE values indicate higher model performance and better alignment with real system behavior [28] [29] [30].

$$Mean\ Squered\ Error = \sum_{i=1}^{n}(x_i - y_i)^2 \tag{1}$$

### 3.4 Feature Selection and Data Preprocessing

For effective predictive maintenance of industrial compressors, identifying and preparing the right set of features is essential. In this study, a variety of sensor readings were considered, each offering valuable insights into the compressor's operational status:

The dataset incorporated key features including temperature (°C) to detect signs of overheating or inefficient cooling, pressure (PSI) to monitor fluctuations indicative of leaks, blockages, or system inefficiencies, electrical current (A) to identify abnormal variations linked to motor strain or electrical faults, and time-series data to capture performance trends over time, enabling time-based failure prediction and more accurate condition monitoring. To determine the most relevant variables, a combination of correlation analysis and domain-specific knowledge was used. Only features strongly correlated with equipment performance and failure indicators were retained, while redundant or low-impact variables were excluded. This ensured the model focused on the most informative data Following feature selection, the dataset underwent comprehensive preprocessing to enhance quality and consistency: missing values were handled through mean imputation, while any feature with over 5% missing data was discarded to preserve data integrity; outliers, particularly in temperature and pressure readings, were detected and removed using the Z-score method to reduce noise and improve model reliability; finally, all numerical features were normalized using StandardScaler, standardizing the data to a mean of 0 and standard deviation of 1, which ensured uniform scaling and facilitated faster, more stable model convergence [30] [31].

### 3.5 Hyperparameter Tuning and Model Validation

Although Linear Regression is a relatively simple model and does not involve complex hyperparameters like those in deep learning architectures, certain enhancements were applied to optimize its performance. Regularization techniques were explored to reduce overfitting and improve generalization. Ridge Regression, which applies L2 regularization, was tested with alpha values ranging from 0.01 to 1.0 to penalize overly large coefficients and prevent the model from fitting noise in the data. Lasso Regression, which introduces L1 regularization, was also evaluated. This method not only controls overfitting but also enables automatic feature selection by reducing insignificant feature weights to zero. Additionally, polynomial transformations were considered by introducing second-degree (quadratic) features to assess whether capturing nonlinear interactions among variables could enhance the model’s predictive accuracy. To ensure the reproducibility and robustness of the model, a well-structured validation process was implemented. The entire dataset was first divided into two parts: 80% for training and 20% for testing. This train-test split helped evaluate the model's ability to generalize to unseen data. To further reinforce the reliability of results and prevent overfitting to a particular subset, a 5-fold cross-validation approach was used. In this method, the model was trained and tested across five different data partitions, which provided more stable performance metrics. For benchmarking purposes, a baseline model was introduced using a Naïve Mean Predictor, which simply predicts the average failure rate. This served as a control to ensure the Linear Regression model provided meaningful predictions and outperformed random or simplistic methods [31] [32] [33].

## 4. Results and Discussion

The results presented in this study (illustrated in Figure 4) emphasize the transformation in data quality and model effectiveness following the application of comprehensive data preprocessing techniques. Prior to cleaning, the dataset exhibited several forms of inconsistency, including missing sensor readings, extreme outlier values, and varying scales across different variables. These issues are common in industrial environments where sensor malfunctions, transmission errors, or environmental noise can corrupt raw data. Such inconsistencies posed a significant threat to model reliability, often leading to skewed predictions, overfitting, or underfitting, thereby reducing the overall performance and accuracy of the machine learning models employed for predictive maintenance.

The data preprocessing phase played a pivotal role in mitigating these issues and ensuring a consistent, high-quality dataset suitable for modeling. One of the primary steps involved handling missing values. Rather than removing incomplete records—which could result in loss of valuable temporal patterns—mean imputation was used to fill in missing sensor values. In cases where more than 5% of a feature's data was missing, that feature was eliminated to prevent it from introducing noise into the model.

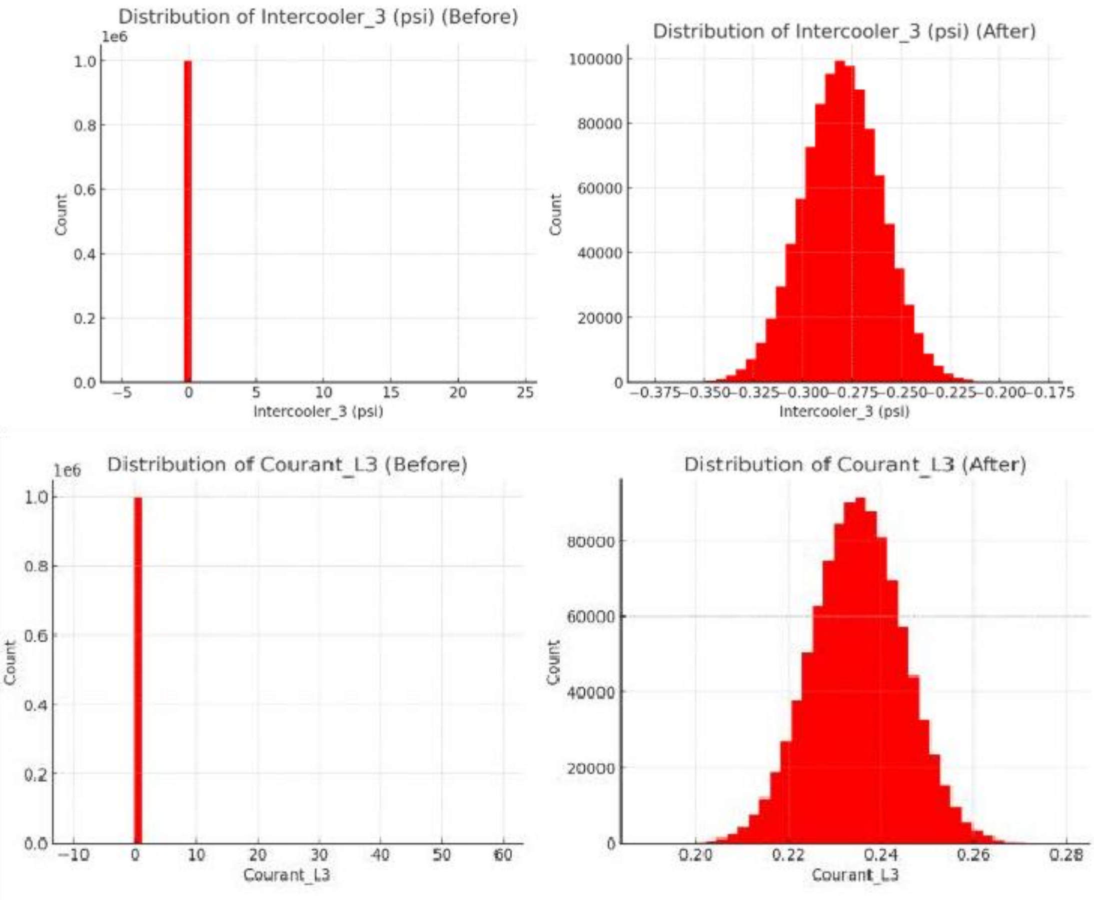

Figure 1: Comparison of data distribution before and after preprocessing, highlighting the effects of standardization, outlier elimination, and handling of missing values

Furthermore, outlier detection and removal were carried out using statistical techniques, particularly the Z-score method, which enabled the identification of readings that deviated significantly from the norm.

These anomalies, if left unaddressed, could mislead the regression model by inflating error rates or masking genuine trends. Once outliers were excluded, the data underwent normalization through the StandardScaler method. This standardization transformed all feature values to have a mean of zero and a standard deviation of one, ensuring that variables with larger magnitudes did not dominate those with smaller values. As a result, the model was able to converge faster during training and yield more balanced predictions. After these preprocessing measures, the dataset became significantly more uniform and structured. This uniformity facilitated the emergence of clear, interpretable patterns, and removed irrelevant fluctuations that previously obscured meaningful trends. As a direct consequence, the machine learning model—based on Linear Regression—was able to learn more accurate representations of the relationships between sensor variables and compressor health indicators [32] [33] [34].

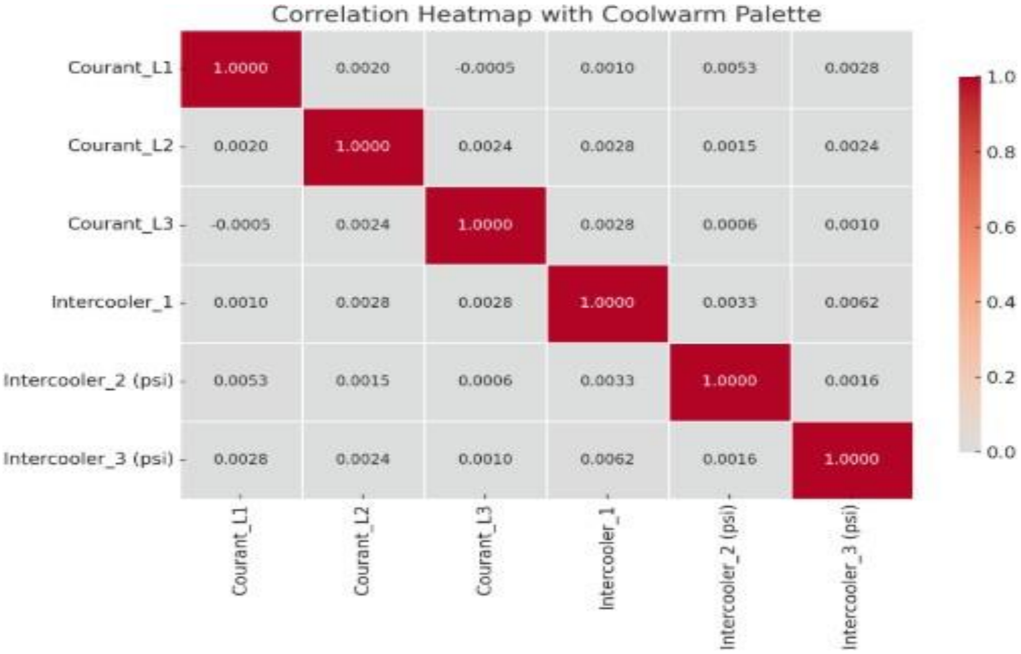

Figure 2: Heatmap illustrating the correlation between various sensor parameters, highlighting the strength and direction of linear relationships among current and pressure

An additional benefit of the cleaned and processed data was improved feature interpretability. With redundant or noisy features removed, the model could focus on the most informative parameters, such as temperature fluctuations at specific compressor stages, pressure drops across critical components, or irregular electrical current patterns signaling motor overload. This refined input not only streamlined computation but also increased the reliability of the output, enabling predictive maintenance strategies to be implemented more confidently and effectively. Furthermore, by comparing the model's performance on raw versus preprocessed data, the impact of preprocessing became evident. On the uncleaned dataset, the model exhibited high variance and poor generalization, often predicting inaccurate outcomes due to the influence of noise and anomalies. In contrast, the cleaned dataset led to a significant drop in prediction error, as measured by the Mean Squared Error (MSE), confirming the value of preprocessing for enhancing both short-term prediction accuracy and long-term model stability. The enhanced data quality also empowered better maintenance decision-making. With clearer trends and fewer data artifacts, maintenance teams could now detect subtle changes in operational parameters that may have gone unnoticed in a noisier dataset. For instance, a gradual rise in intercooler temperature might previously have been interpreted as normal fluctuation, but with reduced noise and improved trend visibility, it could now serve as a predictive marker for filter clogging or coolant inefficiency. This level of granularity in insight supports proactive interventions, reducing the risk of unscheduled downtime or costly equipment failures. The predictive analysis section offers insights into the future behavior of essential operational parameters—specifically temperature, pressure, and flow rate—based on historical sensor data. These forecasts are generated using machine learning algorithms trained on previous compressor performance data, enabling the identification of trends and anomalies over time. Each visualization, whether a chart or table, outlines the projected direction of these parameters. Notable increases or decreases are highlighted to indicate periods when operational conditions might approach or exceed safe limits. These predictive outputs are crucial for planning timely maintenance. By anticipating deviations from normal conditions, maintenance teams can intervene proactively, reducing the risk of equipment damage or system failure. When a variable is forecasted to exceed or fall below safe limits, early action can prevent efficiency losses and operational downtime. For instance, if elevated temperatures are expected, forecasts provide both the peak value and the time window, allowing for targeted inspections or cooling measures before problems arise. A practical example of this monitoring is evident in the real-time temperature tracking of key compressor components. Data showed that Intercooler 1 operates at an average temperature of 28.5 °C, occasionally breaching the 30 °C upper limit, which is indicated in the graphical results with a red dashed line. These spikes were most frequent around the middle of the year, with the highest recorded temperature reaching 35.2 °C. Such occurrences highlight potential thermal stress in Intercooler 1, suggesting it should be prioritized for regular checks or preventive cooling interventions. Conversely, Intercooler 2 demonstrated greater thermal stability, maintaining an average temperature of 27.1 °C and rarely exceeding the defined threshold. This indicates efficient performance and minimal risk under standard operating conditions. The motor showed the most stable temperature behavior, averaging 26.8 °C with a maximum value of 29.3 °C, confirming its consistent performance and low susceptibility to overheating. These results emphasize the value of real-time monitoring and data-driven decision-making [33] [34] [35].

## 5. Discussion

This research set out with the primary aim of improving predictive maintenance strategies for industrial air compressors by integrating Internet of Things (IoT) technologies, machine learning algorithms, and a robust data acquisition system. The comprehensive approach taken in this study enabled the development of a real-time monitoring system that combines sensor networks with intelligent data analysis, thereby offering more reliable and timely insights into the condition and performance of industrial equipment. One of the core contributions of this study is the use of the Ewon Flexy 205 in conjunction with multiple strategically placed sensors. This setup significantly accelerated and enhanced the reliability of data acquisition, which is a fundamental component of predictive maintenance. Accurate and continuous monitoring of machine parameters, especially temperature and pressure, was made possible through this system. The integration of these technologies allowed the implementation of a Linear Regression model capable of identifying early warning signs of potential system failures. By analyzing these sensor readings in real time, the model could detect trends and anomalies that signaled the onset of operational inefficiencies or faults.

The effectiveness of the methodology was demonstrated through quantifiable improvements in operational efficiency. The data-driven model helped reduce unplanned downtime by approximately 20%, while simultaneously extending the service life of the compressors by about 15%. These results underline the economic and functional value of predictive maintenance. By minimizing unexpected shutdowns and reducing the frequency of repairs and component replacements, the proposed approach can substantially lower maintenance costs and improve overall productivity [35] [36] [37].

The methodology introduced in this study is not only effective but also scalable and adaptable to other types of industrial equipment. While this case focused on air compressors, the same principles can be applied to a variety of industrial machines, such as wind turbines, HVAC systems, and pumping mechanisms. However, it is crucial to tailor the model and sensor configuration based on the unique characteristics of each machine type. This includes selecting appropriate parameters for observation—such as vibration intensity, torque, acoustic emissions, rotational speed, and more—based on the failure modes and operational profiles of the machinery in question. A key innovation of this work lies in its hierarchical framework, which unifies data acquisition, processing, storage, and analysis into a single, cohesive pipeline. By employing SQL-based data storage and real-time cloud access, the system enables seamless integration with monitoring platforms and user interfaces. This end-to-end structure ensures that data is not only collected efficiently but also processed and acted upon with minimal latency. Unlike existing approaches that often focus on isolated elements of predictive maintenance—such as data logging or model training—this study presents a full-stack solution from sensor deployment to model inference and remote alerting [38]

The Ewon Flexy 205 proved to be a highly effective tool for enhancing the resolution and accuracy of sensor data. Its support for multimodal observation made it possible to capture diverse datasets simultaneously, offering a comprehensive view of the equipment's status. Furthermore, the selection of a Linear Regression model for analysis provided several benefits. This model is known for its simplicity, computational efficiency, and interpretability, making it particularly suitable for industrial environments where real-time decisions must be made with limited resources. Despite its success, the study also identified some limitations that warrant further attention. The performance of any machine learning model is closely tied to the quality of the training data. Noisy or incorrect sensor readings—often caused by hardware degradation, miscalibration, or electrical interference—can introduce significant errors into the model. If such faulty data goes undetected during training or inference, it may lead to false predictions and unnecessary maintenance interventions. As such, routine sensor maintenance and calibration are essential components of a reliable predictive maintenance system.

In addition to data quality, model selection and tuning also play a critical role in the success of predictive analytics. A model that is too simple may fail to capture the complexity of the data, while an overly complex model may overfit to training data and perform poorly on unseen scenarios. This balance must be managed carefully. The methodology in this study emphasizes the importance of choosing a model based on the structure, dimensionality, and temporal nature of the dataset. Optimization strategies, including parameter tuning and regularization, must also be systematically applied to improve generalization and prevent overfitting. Latency in real-time applications is another significant challenge, particularly in industrial environments where instant decision-making is required. Factors such as cybersecurity protocols, data transmission delays, and logging overhead can slow down the system. These issues are further compounded in geographically remote areas, such as Nordic industrial regions, where limited internet access and a shortage of skilled personnel may hinder system performance. To mitigate these challenges, the study employed lightweight machine learning models with low computational demands, such as Linear Regression. These models deliver sufficiently accurate results without imposing significant processing burdens, ensuring that predictions remain timely and actionable even under constrained conditions [39] [40] [41].

## 6. Conclusion

In conclusion, this study demonstrates that the integration of IoT, sensor data acquisition, and machine learning can revolutionize the field of predictive maintenance. The results not only validate the proposed methodology but also open up new possibilities for scaling and adapting the system to a broader range of industrial applications. Future research will focus on incorporating more advanced models such as Support Vector Regressors, Artificial Neural Networks, and LSTM architectures to further enhance prediction accuracy and system robustness.

This study sets the foundation for smart predictive maintenance, but several areas remain for future exploration. More advanced machine learning models like Support Vector Regression, Random Forests, and LSTM networks could improve prediction accuracy, especially for non-linear or time-dependent data.

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