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DATA-DRIVEN FAULT PREDICTION FRAMEWORK FOR PLC-BASED AUTOMATIC STORAGE/ RETRIEVAL SYSTEM USING ADVANCED MACHINE LEARNING TECHNIQUES

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ABSTRACT:

PLC-based Automatic Storage and Retrieval Systems (AS/RS) are widely used in modern industrial automation to enhance warehouse efficiency and accuracy; however, these systems often suffer from unexpected faults due to mechanical wear, sensor failures, and control system issues, leading to downtime and reduced productivity. Traditional maintenance strategies are not effective for early fault detection, creating a need for a data-driven predictive approach. This study proposes a machine learning-based fault prediction framework using operational data collected from PLC sensors, including parameters such as motor current, position signals, load variations, and error logs. The collected data is pre-processed using techniques like normalization, noise filtering, and feature extraction to ensure data quality. Advanced machine learning algorithms such as Random Forest, Support Vector Machine (SVM), Artificial Neural Networks (ANN), and Gradient Boosting are implemented and evaluated using performance metrics like accuracy, precision, recall, and F1-score. The proposed system aims to detect faults at an early stage, thereby reducing downtime and improving system reliability and efficiency. Validation is carried out using real-time or simulated AS/RS data, demonstrating the effectiveness of the framework in predictive maintenance. Overall, the study contributes to the development of intelligent, data-driven solutions for industrial automation, supporting smart manufacturing and Industry 4.0 initiatives by enabling proactive maintenance and optimized operational performance.

Keywords*: PLC-based Automation, Automatic Storage and Retrieval System (AS/RS), Fault Prediction, Predictive Maintenance, Machine Learning, Industrial IoT (IIoT), Data-Driven Modeling, Sensor Data Analytics, Condition Monitoring, Smart Manufacturing*

INTRODUCTION

In recent years, the evolution of industrial automation has been significantly driven by the integration of advanced technologies such as Programmable Logic Controllers (PLC), Industrial Internet of Things (IIoT), cyber-physical systems, and smart manufacturing frameworks. PLC-based Automatic Storage and Retrieval Systems (AS/RS) have emerged as critical components in modern warehouse automation due to their capability to ensure high-speed, accurate, and efficient material handling operations. These systems operate through continuous monitoring and control of mechanical and electrical subsystems using real-time sensor data and communication networks. [Gnana Swathika et al., 2024] However, despite their advantages, PLC-based systems are susceptible to faults caused by synchronization errors, sensor inaccuracies, communication delays, and mechanical degradation, which can severely impact system reliability and operational efficiency [Ayah Hijazi et al., 2024]. The rapid advancement of Industry 4.0 has further increased the complexity and data intensity of industrial systems, necessitating the adoption of intelligent and autonomous fault detection mechanisms. Conventional maintenance strategies, including corrective and preventive maintenance, are largely reactive in nature and fail to detect early-stage anomalies in dynamic industrial environments. These limitations often lead to unexpected equipment failures, increased downtime, and higher operational costs. Recent research highlights the importance of data-driven and machine learning-based approaches for predictive maintenance, which utilize historical and real-time data to identify hidden patterns and predict potential system failures before their occurrence [Heiko Webert et al., 2025]

Machine learning techniques have gained considerable attention in fault prediction and condition monitoring due to their ability to process large-scale, high-dimensional industrial datasets and extract meaningful insights. Algorithms such as Random Forest, Support Vector Machine (SVM), Artificial Neural Networks (ANN), and deep learning models have demonstrated superior performance in detecting anomalies and classifying fault conditions. [Pooya Sajjadi et al., 2025] For instance, machine learning-based models applied to industrial systems, such as induction motors and chemical processes, have achieved high prediction accuracy and reliability, enabled early fault detection and reduced maintenance costs.

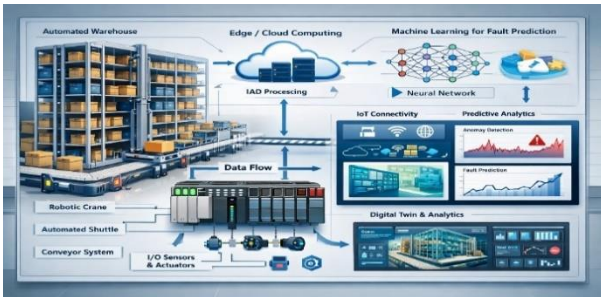

Figure 1.1: PLC-Based Automatic Storage and Retrieval System (AS/RS) Integrated with Machine Learning for Fault Prediction in an Industry 4.0 Environment

These approaches not only improve fault diagnosis capabilities but also support the development of intelligent maintenance systems capable of adapting to changing operational conditions [Ademola Abdulkareem et al., 2025] In addition, the integration of data-driven methodologies with emerging technologies such as digital twins, edge computing, and intelligent monitoring systems has further enhanced the capabilities of industrial fault prediction frameworks. Digital twin-based systems enable real-time synchronization between physical assets and virtual models, allowing continuous monitoring, simulation, and optimization of system performance. [Husnain Ali et al., 2024]. Similarly, advanced data-driven frameworks incorporating techniques such as drift detection, anomaly detection, and continuous learning provide improved robustness and adaptability in heterogeneous industrial processes. Despite these advancements, several challenges remain, including data quality issues, lack of standardized frameworks, model interpretability, and integration complexity within existing PLC-based systems [Julien Chapelin et al., 2025]

Therefore, there is a critical need to develop an efficient and scalable data-driven fault prediction framework specifically tailored for PLC-based Automatic Storage and Retrieval Systems. This study aims to address these challenges by leveraging advanced machine learning techniques to analyze operational data and detect faults at an early stage. The proposed framework focuses on improving system reliability, minimizing downtime, and optimizing maintenance strategies through intelligent data analytics. By integrating machine learning with industrial automation systems, the research contributes to the advancement of predictive maintenance solutions and supports the broader vision of smart manufacturing and Industry 4.0 ecosystems. [Christina Latsou et al., 2024].

1.1 Background of PLC-Based AS/RS

The evolution of industrial automation has significantly reshaped modern warehousing and logistics systems, leading to the widespread adoption of advanced technologies such as Programmable Logic Controllers (PLC), Industrial Internet of Things (IIoT), and cyber-physical systems. Among these innovations, Automatic Storage and Retrieval Systems (AS/RS) have emerged as a key solution for improving warehouse efficiency, accuracy, and operational speed. PLC-based AS/RS integrates mechanical handling systems with intelligent control units to automate storage and retrieval processes with minimal human intervention. These systems rely on real-time data acquisition, sensor feedback, and precise control logic to ensure smooth and synchronized operations across multiple subsystems. The increasing demand for high-throughput logistics, reduced operational errors, and optimal space utilization has further accelerated the deployment of PLC-controlled AS/RS in industries such as manufacturing, e-commerce, and distribution centers. [Pooya Sajjadi et al., 2025]. However, as these systems become more complex and data-intensive, they are increasingly vulnerable to faults arising from mechanical wear, electrical failures, sensor inaccuracies, and communication delays. Such faults can lead to system downtime,

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reduced efficiency, and increased maintenance costs. Traditional maintenance strategies, including reactive and preventive approaches, are often insufficient in addressing these challenges, as they fail to provide early fault detection and real-time system insights. Recent advancements in data-driven technologies and machine learning have highlighted the potential for predictive maintenance solutions that can analyze historical and real-time data to detect anomalies and predict failures before they occur. These approaches not only enhance system reliability but also contribute to cost-effective and efficient operations in automated environments [Gnana Swathika et al., 2024; Heiko Webert et al., 2025] Overview of Automation in Warehousing Warehouse automation has become a fundamental component of modern supply chain management, enabling organizations to handle increasing demands for speed, accuracy, and efficiency. Automation in warehousing involves the integration of advanced technologies such as robotics, conveyor systems, sensors, and intelligent control systems to perform tasks including storage, retrieval, sorting, and inventory management. Unlike traditional manual systems, automated warehouses operate with minimal human intervention, significantly reducing labor costs and human errors while improving operational consistency. [Leonardo Maretto et al., 2023]. The adoption of IoT-based devices and real-time monitoring systems has further enhanced warehouse automation by enabling continuous data collection, process optimization, and dynamic decision-making.

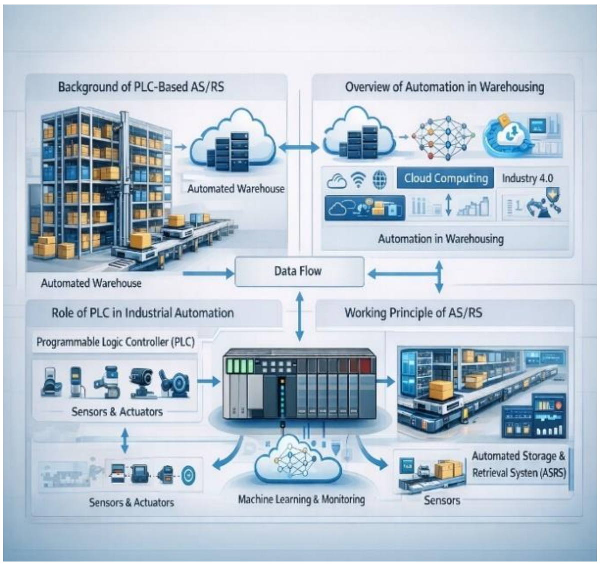

Figure 1.2: Block Diagram of PLC-Based Automatic Storage and Retrieval System (AS/RS) with Data Flow and Industry 4.0 Integration

In recent years, the concept of smart warehouses has gained prominence, where automation is combined with data analytics and machine learning to create intelligent and adaptive systems. [Tamíris Pacheco Da Costa et al., 2024] These systems can analyze large volumes of operational data to identify inefficiencies, optimize resource allocation, and predict potential system failures. For instance, real-time monitoring and data-driven analytics enable early detection of anomalies, thereby preventing unexpected breakdowns and improving system reliability. However, the increasing reliance on data-intensive systems also introduces challenges related to data management, system integration, and fault detection. Ensuring the accuracy, consistency, and reliability of sensor data is critical for maintaining efficient warehouse operations. Therefore, there is a growing need for advanced fault prediction frameworks that can effectively utilize data for improving performance and reducing downtime in automated warehouse environments [Mohsen Soori et al., 2023] Role of PLC in Industrial Automation Programmable Logic Controllers (PLCs) are one of the most essential components in industrial automation systems, providing reliable and real-time control of machines and processes. PLCs are designed to operate in harsh industrial environments and are widely used due to their robustness, flexibility, and ease of programming. They function by continuously monitoring input signals from sensors, executing control logic based on programmed instructions, and generating output signals to control actuators such as motors, valves, and conveyors. In PLC-based AS/RS, the PLC acts as the central control unit, ensuring proper coordination between various subsystems, including storage racks, cranes, conveyors, and sensors. [Xiaoxia Zhang et al., 2025]. Modern PLC systems are equipped with advanced communication capabilities, enabling integration with supervisory control systems such as SCADA and cloud-based platforms. This integration facilitates real-time monitoring, data

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acquisition, and remote control of industrial processes. Additionally, PLCs play a crucial role in ensuring system safety, synchronization, and efficient operation. However, despite their advantages, PLC-based systems face challenges such as data loss, synchronization delays, and limited fault diagnosis capabilities. These issues can affect system performance and lead to unexpected failures if not addressed promptly. Recent research has emphasized the integration of machine learning techniques with PLC systems to enhance fault detection and predictive maintenance capabilities. By leveraging data-driven approaches, PLC systems can be transformed into intelligent control units capable of identifying anomalies and improving overall system reliability [Gnana Swathika et al., 2024; Ayah Hijazi et al., 2024] Working Principle of AS/RS The Automatic Storage and Retrieval System (AS/RS) operate on the principle of automated material handling using computer-controlled mechanisms to store and retrieve items efficiently. The system typically consists of storage racks, automated cranes or shuttle systems, conveyors, sensors, and a centralized control unit such as a PLC. When a storage or retrieval request is generated, the control system processes the command and determines the optimal path for the handling equipment. [Julien Chapelin et al., 2025]. The automated crane or shuttle then moves to the designated location, retrieves or stores the item, and returns to its original position. Sensors continuously monitor parameters such as position, load, speed, and system status, providing real-time feedback to ensure accurate and synchronized operations. Advanced AS/RS systems incorporate intelligent algorithms and data-driven techniques to optimize system performance, reduce cycle time, and improve throughput. For example, machine learning models can be used to predict demand patterns, optimize routing, and detect anomalies in system behavior. Additionally, simulation-based optimization and neural network-assisted models have been developed to enhance decision-making and operational efficiency in AS/RS environments. [Heiko Webert et al., 2025] Despite these advancements, the integration of multiple mechanical, electrical, and control components makes AS/RS systems highly complex and prone to faults. Mechanical wear, sensor failures, and control system errors can disrupt operations and lead to significant productivity losses. Therefore, implementing a data-driven fault prediction framework is essential for ensuring system reliability, minimizing downtime, and supporting predictive maintenance strategies in automated warehouse systems [Andrea Ferrari et al., 2025]

Figure 1.3: Data-Driven Fault Prediction Framework for PLC-Based Automatic Storage and Retrieval System (AS/RS)

INTRODUCTION TO FAULT PREDICTION IN INDUSTRIAL SYSTEMS

Fault prediction in industrial systems has become a fundamental requirement in modern manufacturing environments driven by Industry 4.0 and smart automation. Industrial systems today are equipped with numerous sensors, PLCs, and communication networks that continuously generate large volumes of operational data. This data provides valuable insights into system performance, enabling the detection of anomalies and prediction of potential failures before they occur. Fault prediction focuses on identifying early warning signs of system degradation using advanced data analytics and machine learning techniques. [Hassan N. Noura et al., 2025].

Unlike traditional maintenance strategies, which are reactive or schedule-based, predictive approaches allow industries to take proactive actions, thereby reducing unexpected downtime, improving operational efficiency, and minimizing maintenance costs. The integration of technologies such as Industrial Internet of Things (IIoT), cloud computing, and edge analytics has further enhanced the capability of fault prediction systems by enabling real-time monitoring and decision-making. Machine learning models can analyze complex patterns and relationships within high-dimensional datasets, making them suitable for dynamic industrial environments. Additionally, prognostics and health management (PHM) frameworks provide structured methodologies for fault prediction by combining data acquisition, feature extraction, and predictive modeling. Despite these advancements, challenges such as data quality, scalability, and model interpretability remain critical issues that must be addressed for effective implementation in real-world applications [Pooya Sajjadi et al., 2025; Heiko Webert et al., 2025]

2.1 Overview of AS/RS Faults

Automatic Storage and Retrieval Systems (AS/RS) are complex automated systems that integrate mechanical components, electrical systems, PLC controllers, and communication networks to perform efficient material handling operations. Due to this integration, AS/RS systems are prone to a wide range of faults that can significantly affect system performance and reliability. These faults may result in increased cycle time, reduced throughput, and even complete system shutdowns, leading to economic losses in industrial operations. Therefore, understanding the nature and classification of faults is essential for designing effective fault prediction and maintenance strategies. The complexity of AS/RS increases with system scale and operational demands, where multiple subsystems operate simultaneously in a coordinated manner. Faults in one subsystem can propagate and affect the overall system performance, making fault diagnosis a challenging task. Recent research emphasizes the importance of data-driven fault classification and predictive maintenance frameworks that can analyze system behavior in real time and identify potential failures. The use of digital twin technology further enhances fault detection by enabling real-time simulation and monitoring of system operations, providing deeper insights into system performance and reliability [Andrea Ferrari et al., 2025] Mechanical failures are one of the most common types of faults in AS/RS systems due to continuous operation and heavy load handling. These failures include wear and tear of moving parts, misalignment of cranes, conveyor belt failures, bearing damage, and structural fatigue. Over time, these issues can degrade system performance and lead to unexpected breakdowns if not detected early. Monitoring mechanical parameters such as vibration, temperature, and load conditions is essential for identifying early signs of failure. [Julien Chapelin et al., 2025]. Advanced predictive maintenance techniques use machine learning algorithms to analyze sensor data and detect patterns associated with mechanical faults. For example, vibration analysis combined with data-driven models can accurately predict bearing failures and misalignment issues. These approaches not only improve system reliability but also reduce maintenance costs by enabling timely interventions. The integration of intelligent monitoring systems with AS/RS enhances the ability to detect mechanical faults at an early stage, ensuring smooth and efficient system operation [Andrea Ferrari et al., 2025] Electrical and PLC-related faults significantly impact the performance of AS/RS systems, as PLCs serve as the central control units responsible for coordinating system operations. These faults include power supply fluctuations, hardware malfunctions, control logic errors, and communication delays within PLC networks. Such issues can lead to incorrect system behavior, loss of synchronization between components, and potential system failures. Modern PLC systems are integrated with communication networks and supervisory control systems, making them more complex and susceptible to faults. Data inconsistencies, timing delays, [Samuel M. Gbashi et al., 2025]. and communication failures can disrupt real-time operations and reduce system efficiency. Recent research highlights the use of machine learning and neural network-based approaches to enhance fault detection in PLC systems. These techniques can analyze operational data to identify anomalies and predict potential failures, improving system reliability and reducing downtime [Gnana Swathika et al., 2024] Sensors and communication systems are critical components of AS/RS, providing real-time data required for monitoring and control. However, faults such as sensor drift, noise, calibration errors, data loss, and communication failures can lead to inaccurate data and unreliable system performance. These errors can propagate through the control system, resulting in incorrect decisions and potential system failures. Ensuring data accuracy and reliability is essential for effective fault prediction. Advanced data preprocessing techniques, including filtering, normalization, and anomaly detection, are used to improve data quality. Additionally, IoT-based communication protocols and real-time monitoring systems enhance data transmission reliability. The integration of machine learning models with sensor data further improves fault detection capabilities by identifying patterns and anomalies that may not be detectable using traditional methods [Tamíris Pacheco Da Costa et al., 2024; Sofia Ahmed et al., 2024].

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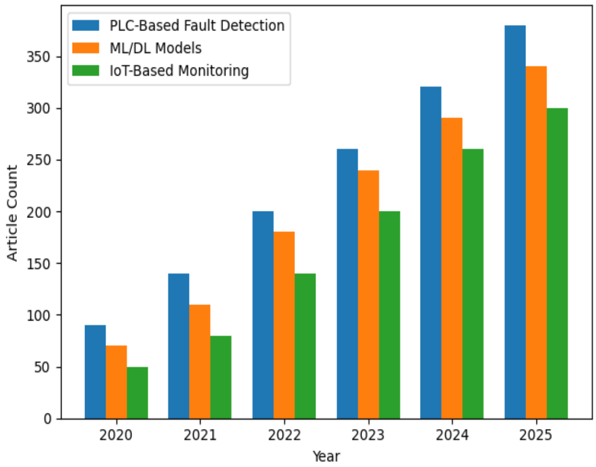

Figure 1.4: Literature Statistics on Fault Prediction in PLC-Based Automatic Storage and Retrieval Systems (AS/RS)

2.2 Traditional Fault Detection Techniques

Traditional fault detection techniques have been widely used in industrial systems due to their simplicity and ease of implementation. However, these methods are limited in their ability to handle complex and dynamic systems. They are generally based on predefined rules, thresholds, and periodic inspections, which may not capture the underlying patterns of system behavior. Rule-based systems detect faults by comparing system parameters with predefined thresholds and conditions. [Ameer H. Sabry et al., 2024] These systems rely heavily on expert knowledge and are effective for simple and well-defined problems. However, they lack flexibility and cannot adapt to changing system conditions or detect unknown fault patterns. As a result, their effectiveness is limited in modern industrial environments where systems are highly dynamic and complex [Dajun Du et al., 2023]. Preventive maintenance involves performing maintenance activities at regular intervals based on time or usage. While this approach reduces the risk of unexpected failures, it does not consider the actual condition of the system, leading to unnecessary maintenance and increased costs. Moreover, it cannot predict failures accurately, making it less efficient compared to predictive maintenance approaches that utilize real-time data and advanced analytics [Pere Marti-Puiga et al., 2024]

2.3 Machine Learning Techniques in Fault Prediction

Machine learning techniques have significantly improved fault prediction by enabling systems to learn from data and identify complex patterns associated with faults. These techniques are highly effective in handling large-scale and high-dimensional datasets, making them suitable for industrial applications. Supervised learning models are trained using labeled datasets to classify and predict faults. Algorithms such as Decision Trees, Random Forest, and Support Vector Machines (SVM) have demonstrated high accuracy in identifying known fault conditions. These models are widely used due to their interpretability and effectiveness; however, their performance depends on the availability of high-quality labeled data [Ademola Abdulkareem et al., 2025]. Unsupervised learning models are used for anomaly detection in cases where labeled data is not available. These models identify patterns and deviations in data using techniques such as clustering and principal component analysis. They are particularly useful for detecting unknown faults in complex systems, although they may require additional validation for accurate interpretation [Sen Yang et al., 2025]. Deep learning approaches, such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, are capable of analyzing complex and time-series data. These models automatically extract features and capture temporal dependencies, making them highly effective for fault prediction. However, they require large datasets and high computational resources, which can be a limitation in some industrial applications [Junyu Guo et al., 2024; Yuhan Liu et al., 2025].

2.4 Data-Driven Approaches in Industrial Automation

Data-driven approaches utilize real-time and historical data to monitor system performance, detect anomalies, and predict faults. These approaches integrate machine learning models, sensor data, and analytics tools to create intelligent systems capable of self-learning and adaptation. Christina Latsou et al., 2024] Technologies such as digital twins and IoT further enhance data-driven frameworks by enabling real-time simulation and monitoring of industrial processes. Despite their advantages, challenges such as data quality, integration complexity, and model

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interpretability remain significant barriers. Ensuring reliable and accurate data is essential for effective fault prediction, as poor data quality can lead to incorrect predictions. Addressing these challenges is crucial for the successful implementation of data-driven fault prediction systems in industrial automation [Julien Chapelin et al., 2025]

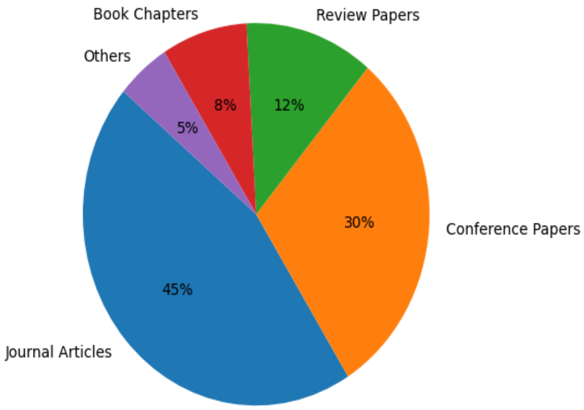

Figure 1.5: Publication Distribution in PLC-Based AS/RS Fault Prediction Research

2.5 Comparative Analysis of Existing Methods

A comparative analysis of existing fault detection methods highlights the differences between traditional and machine learning-based approaches. Traditional methods are simple and cost-effective but lack the ability to detect complex and early-stage faults. In contrast, machine learning approaches provide higher accuracy, adaptability, and predictive capabilities by analyzing large datasets and identifying hidden patterns. [Pooya Sajjadi et al., 2025] However, machine learning methods require high-quality data, computational resources, and technical expertise for implementation. Recent research suggests that hybrid approaches, combining traditional methods with machine learning techniques, can provide optimal performance by leveraging the strengths of both approaches. These integrated systems are expected to play a crucial role in the future of industrial fault prediction, supporting the development of intelligent and autonomous manufacturing systems [Heiko Webert et al., 2025]

Table 1. Literature Review on Data-Driven Fault Prediction in PLC-Based AS/RS

Ref.	**Year**	**Data Modality**	**Objective / Scope**	**Technique / Architecture**	**Explainability**	**Federated Learning**	**Key Findings**	**Research Gaps and Open Challenges**
[1]	2025	Sensor Data (Vibration, Temperature)	Fault prediction in industrial systems	Random Forest, SVM	Limited	No	High accuracy in fault classification	Lack of real-time implementation
[2]	2024	PLC + IoT Data	Predictive maintenance in automation	ANN, IoT Framework	Moderate	No	Improved system monitoring	Data quality and integration issues
[3]	2025	Time-Series Data	Early fault detection	LSTM, Deep Learning	Low	No	Effective for sequential data	Requires large dataset
[4]	2024	Multi-Sensor Data	Anomaly detection in AS/RS	K-Means, PCA	Low	No	Detects unknown faults	Poor interpretability
[5]	2025	Edge + Sensor Data	Real-time fault prediction	Edge AI, CNN	Moderate	Partial	Reduced latency and fast detection	Computational complexity

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[6]	2023	Industrial Big Data	Predictive analytics	Hybrid ML Models	Moderate	Yes	Improved privacy and scalability	Communication overhead
[7]	2024	IoT Sensor Data	Smart warehouse monitoring	IoT + ML Integration	Low	No	Enhanced automation	Security concerns
[8]	2025	PLC Logs + Sensor Data	Fault diagnosis in control systems	Neural Networks	Low	No	Accurate fault detection	Lack of explainability
[9]	2024	Real-Time Streaming Data	Online fault detection	Stream Learning Models	Moderate	Partial	Continuous monitoring capability	Model drift issues
[10]	2025	Multi-modal Data	Intelligent fault prediction	Hybrid Deep Learning	Low	Yes	High prediction performance	High computational cost

SYNTHESIS OF PREVIOUS RESEARCH

Recent studies in industrial fault prediction highlight a significant shift from traditional maintenance strategies toward intelligent, data-driven approaches enabled by machine learning and Industry 4.0 technologies. Early research primarily focused on rule-based and model-driven techniques, which relied heavily on expert knowledge and predefined thresholds for fault detection. However, these approaches were limited in handling complex, nonlinear, and dynamic industrial environments, leading to the adoption of data-driven methods that utilize real-time sensor data and advanced analytics for improved fault prediction accuracy [3-7] The integration of machine learning techniques has played a crucial role in enhancing predictive maintenance systems across various industrial domains. Supervised learning models such as Support Vector Machines (SVM), Decision Trees, and Random Forest have been widely used for fault classification, demonstrating high accuracy when sufficient labeled data is available. On the other hand, unsupervised learning methods, including clustering and anomaly detection techniques, have proven effective in identifying unknown and rare faults without requiring labeled datasets. Recent advancements in deep learning, particularly Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, have further improved fault prediction by capturing complex temporal and spatial patterns in industrial data [5-22].

Moreover, the emergence of Industrial Internet of Things (IIoT) and cyber-physical systems has enabled continuous data acquisition and real-time monitoring of industrial processes. These technologies facilitate the implementation of predictive maintenance frameworks by providing large volumes of high-dimensional data for analysis. Studies have shown that the use of IoT-based monitoring systems combined with machine learning algorithms can significantly reduce downtime and maintenance costs while improving system reliability and efficiency [1-27]. Additionally, cloud and edge computing architectures have been introduced to support real-time fault detection and scalable data processing, further enhancing the performance of predictive systems [11-30]. Despite these advancements, several challenges remain in the development and deployment of fault prediction systems. One of the major issues is the availability and quality of labeled data, as industrial fault datasets are often imbalanced and limited. This has led to the exploration of hybrid and transfer learning approaches that can improve model generalization and performance across different operating conditions. Furthermore, the lack of interpretability in complex machine learning models, particularly deep learning, has raised concerns regarding trust and transparency in industrial applications, emphasizing the need for Explainable AI (XAI) techniques [2-14]

In addition, recent research emphasizes the importance of hybrid approaches that combine traditional signal processing techniques with machine learning models to achieve better performance and robustness. These approaches leverage domain knowledge and data-driven insights to improve fault detection accuracy and adaptability in complex systems. Data fusion techniques and multi-sensor integration have also been explored to enhance fault diagnosis by combining information from multiple sources, thereby improving decision-making capabilities [4-10] Furthermore, the application of fault prediction techniques in automated systems such as PLC-based AS/RS highlights the growing need for intelligent monitoring frameworks capable of handling real-time data and dynamic operational conditions. While existing studies have demonstrated promising results in fault

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detection and predictive maintenance, most approaches are still limited to laboratory environments or specific industrial applications. Issues such as scalability, integration with existing systems, and real-time deployment remain open challenges that require further research and development [13-19] Overall, the literature indicates that data-driven fault prediction using machine learning is a rapidly evolving field with significant potential for improving industrial automation systems. However, future research should focus on developing scalable, interpretable, and real-time capable frameworks that can be effectively integrated into industrial environments. The incorporation of advanced techniques such as federated learning, digital twins, and edge AI is expected to further enhance the capabilities of fault prediction systems, enabling more reliable and efficient industrial operations [17- 21].

3.1 Data Collection and Acquisition

Data collection and acquisition represent the foundational stage in the proposed data-driven fault prediction framework for PLC-based Automatic Storage and Retrieval Systems (AS/RS). In modern industrial environments, automation systems are equipped with numerous sensors, actuators, and programmable logic controllers (PLCs) that continuously generate large volumes of real-time operational data. This data captures various aspects of system behavior, including mechanical performance, electrical conditions, control signals, and environmental factors. [Heiko Webert et al., 2025] Effective data acquisition ensures that relevant and high-quality data is captured accurately and consistently, which is essential for developing reliable machine learning models for fault prediction. The integration of Industrial Internet of Things (IIoT) technologies has significantly improved data acquisition capabilities by enabling seamless communication between devices and centralized systems. Communication protocols such as OPC-UA, Modbus, and Ethernet/IP facilitate real-time data transfer from PLCs to data storage platforms, allowing continuous monitoring and analysis of system performance. Furthermore, advanced data acquisition systems incorporate edge computing and cloud-based architectures to handle large-scale industrial data efficiently. [Pooya Sajjadi et al., 2025] Edge computing allows preliminary data processing at the source, reducing latency and bandwidth requirements, while cloud platforms provide scalable storage and computational resources for advanced analytics. However, challenges such as data inconsistency, noise, missing values, and synchronization issues across multiple data sources can affect the quality of collected data. Addressing these challenges requires the implementation of robust data validation and filtering techniques during the acquisition stage. A well-designed data collection framework not only improves the reliability of machine learning models but also enhances the overall effectiveness of predictive maintenance strategies in industrial automation systems [Hassan N. Noura et al., 2025] PLC data sources are critical for obtaining real-time insights into the operation and health of AS/RS systems. These sources include input/output (I/O) modules, sensor signals, actuator responses, and system logs generated by the PLC controller. Sensors such as vibration, temperature, pressure, proximity, and load sensors continuously monitor system conditions and provide valuable data for fault analysis. Additionally, PLC logs contain information about system events, alarms, control actions, and error messages, which are essential for identifying abnormal behavior and diagnosing faults. The integration of PLC data with supervisory control systems such as SCADA and external IoT devices further enhances data availability and enables comprehensive system monitoring. [Ayah Hijazi et al., 2024] Moreover, multi-source data integration allows for a more holistic understanding of system behavior by combining data from different subsystems, including mechanical, electrical, and communication components. However, managing heterogeneous data sources and ensuring synchronization across different platforms pose significant challenges. Data fusion techniques and standardized communication protocols are often employed to address these issues and ensure consistent data representation. Efficient handling of PLC data sources is crucial for building accurate and reliable fault prediction models, as it directly impacts the quality and completeness of the dataset used for machine learning applications [Gnana Swathika et al., 2024] The selection of appropriate parameters is a key factor in the success of fault prediction models in PLC-based AS/RS systems. A wide range of parameters is collected to capture different aspects of system behavior, including mechanical, electrical, operational, and environmental variables. Mechanical parameters such as vibration, displacement, speed, and load provide insights into the condition of moving components and help detect issues such as wear, misalignment, and structural fatigue. Electrical parameters, including voltage, current, power consumption, and frequency, are used to monitor the performance of electrical systems and identify faults related to power supply and control units. [Andrea Ferrari et al., 2025] Operational parameters, such as cycle time, position accuracy, throughput, and system status, reflect the overall efficiency and performance of the AS/RS system. Environmental factors such as temperature, humidity, and dust levels may also influence system behavior and are often included in the dataset for comprehensive analysis. Collecting diverse and relevant parameters enables the development of robust machine learning models capable of capturing complex relationships and identifying fault patterns. However, excessive or irrelevant data can increase computational complexity and reduce model efficiency. Therefore, feature selection techniques are

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employed to identify the most significant parameters, ensuring optimal model performance and accuracy [Samuel M. Gbashi et al., 2025] Data logging techniques play a crucial role in storing, organizing, and managing the large volumes of data generated in industrial systems. In PLC-based AS/RS systems, data can be logged locally within PLC memory, on on-premise servers, or on cloud-based platforms for remote access and analysis. Time-stamped data logging ensures accurate synchronization of data from multiple sources, enabling detailed temporal analysis of system behavior and fault patterns. Advanced data logging systems incorporate real-time data streaming and edge computing technologies, which allow data to be processed locally before being transmitted to centralized storage systems. [Christina Latsou et al., 2024] Cloud-based data logging offers significant advantages, including scalability, flexibility, and accessibility, making it suitable for large-scale industrial applications. It also enables integration with advanced analytics tools and machine learning platforms for real-time fault prediction. However, challenges such as data security, privacy, and network reliability must be addressed to ensure the integrity and confidentiality of industrial data. Implementing secure communication protocols and data encryption techniques is essential for protecting sensitive information. Effective data logging ensures that high-quality data is available for model training and analysis, which is critical for the successful implementation of predictive maintenance systems [Julien Chapelin et al., 2025]

3.2 Data Preprocessing

Data preprocessing is a vital step in preparing raw industrial data for machine learning analysis, as real-world datasets often contain noise, missing values, and inconsistencies. In PLC-based AS/RS systems, data collected from sensors and control units may be affected by measurement errors, communication delays, and environmental factors. Preprocessing techniques such as data cleaning, feature extraction, and normalization are used to improve data quality and ensure that the dataset is suitable for analysis. [Tamíris Pacheco Da Costa et al., 2024] These techniques help remove irrelevant or redundant information, reduce dimensionality, and standardize the data format, thereby enhancing the performance and accuracy of machine learning models. In addition, automated preprocessing pipelines are increasingly used in industrial applications to enable real-time data processing and support intelligent decision-making systems. These pipelines integrate multiple preprocessing steps into a single framework, improving efficiency and consistency. Effective preprocessing not only improves model accuracy but also reduces computational complexity and training time. Despite its importance, preprocessing remains a challenging task due to the complexity and variability of industrial data, requiring advanced techniques and domain expertise for optimal implementation [Pooya Sajjadi et al., 2025] Data cleaning involves identifying and correcting errors, inconsistencies, and missing values in the dataset to ensure data reliability and accuracy. Industrial data is often affected by noise due to sensor inaccuracies, signal interference, and environmental disturbances. Techniques such as filtering, interpolation, and outlier detection are used to handle noisy and incomplete data. For example, statistical methods can be used to identify outliers, while interpolation techniques can estimate missing values based on neighboring data points. [Sen Yang et al., 2025]. Ensuring data quality is essential for accurate fault prediction, as poor-quality data can lead to incorrect model predictions and reduced system performance. Advanced data cleaning methods, including machine learning-based anomaly detection techniques, are increasingly used to automate the cleaning process and improve efficiency. These methods can identify complex patterns and detect anomalies that may not be apparent using traditional techniques, thereby enhancing the reliability of the dataset used for model training [Tamíris Pacheco Da Costa et al., 2024] Feature extraction is a critical process in which relevant features are selected and transformed from raw data to improve the performance of machine learning models. Industrial datasets often contain a large number of variables, many of which may be redundant or irrelevant. Techniques such as statistical analysis, principal component analysis (PCA), and domain knowledge-based feature selection are used to identify important features that contribute significantly to fault prediction. [Sen Yang et al., 2025] Effective feature extraction reduces data dimensionality, improves computational efficiency, and enhances the ability of machine learning models to detect patterns and anomalies. It also helps in eliminating noise and irrelevant information, thereby improving model accuracy and robustness. In industrial applications, feature extraction is often combined with feature engineering techniques, which involve creating new features based on domain knowledge to improve model performance. This step is essential for developing efficient and accurate fault prediction systems [Hassan N. Noura et al., 2025] Data normalization ensures that all features in the dataset are scaled to a common range, which is essential for machine learning algorithms that are sensitive to the magnitude of input data. Techniques such as min-max scaling and z-score normalization are commonly used to standardize data. Normalization improves the convergence of machine learning models and ensures that all features contribute equally to the learning process. [Ademola Abdulkareem et al., 2025] In industrial datasets, parameters often have different units and scales, which can lead to bias in model training if not properly normalized. By standardizing the data, normalization enhances model stability and accuracy, making it easier for algorithms to learn patterns and relationships. Proper normalization is particularly

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important for algorithms such as SVM and neural networks, which are sensitive to feature scaling. Implementing effective normalization techniques is therefore essential for achieving reliable and accurate fault prediction results [Yuhan Liu et al., 2025]

3.3 Machine Learning Model Development

Machine learning model development is a core component of the proposed fault prediction framework, involving the selection, training, and evaluation of models capable of identifying fault patterns in industrial data. This stage leverages advanced algorithms to analyze complex relationships and patterns in high-dimensional datasets, enabling accurate fault prediction. The choice of model depends on various factors, including data characteristics, computational requirements, and desired performance metrics. [Heiko Webert et al., 2025] The development process includes model training, testing, and validation, ensuring that the model generalizes well to unseen data. Performance metrics such as accuracy, precision, recall, and F1-score are used to evaluate model effectiveness. The integration of machine learning models with industrial systems enhances predictive maintenance capabilities, enabling real-time fault detection and improving system reliability. Despite their advantages, machine learning models require high-quality data and careful tuning to achieve optimal performance [Pooya Sajjadi et al., 2025] Algorithm Selection (RF, SVM, ANN, etc.) Selecting the appropriate algorithm is essential for achieving optimal performance in fault prediction tasks. Commonly used algorithms include Random Forest (RF), Support Vector Machines (SVM), and Artificial Neural Networks (ANN). Each algorithm has its strengths and limitations; for example, Random Forest is robust and handles high-dimensional data effectively, while SVM is suitable for classification tasks with clear decision boundaries. ANN and deep learning models are capable of capturing complex nonlinear relationships in data, making them suitable for dynamic industrial environments. [Ademola Abdulkareem et al., 2025] The choice of algorithm depends on factors such as dataset size, feature characteristics, and computational resources. In some cases, hybrid models combining multiple algorithms are used to improve performance. Careful selection and evaluation of algorithms are essential for developing efficient and accurate fault prediction systems [Junyu Guo et al., 2024] Model training involves feeding the preprocessed dataset into the selected algorithm to learn patterns and relationships between input features and output labels. The dataset is typically divided into training and testing sets to evaluate model performance and ensure generalization. Cross-validation techniques are used to prevent overfitting and improve model robustness. Testing evaluates the model's ability to predict faults accurately on unseen data using performance metrics such as accuracy, precision, recall, and confusion matrix. Proper training and testing ensure that the model performs reliably in real-world industrial applications. Continuous model evaluation and updating are necessary to maintain performance in dynamic environments where system behavior may change over time [Sen Yang et al., 2025; Yuhan Liu et al., 2025] Hyperparameter tuning is the process of optimizing model parameters to achieve the best possible performance. Techniques such as grid search, random search, and Bayesian optimization are used to identify optimal hyperparameter combinations. Proper tuning improves model accuracy, reduces overfitting, and enhances generalization capability. In industrial applications, hyperparameter optimization is critical for handling complex datasets and achieving high-performance fault prediction models. Automated tuning frameworks and optimization algorithms are increasingly used to improve efficiency and reduce manual effort. Effective hyperparameter tuning ensures that machine learning models deliver reliable and accurate predictions, making them suitable for real-time industrial applications [Heiko Webert et al., 2025].

Table 2: Performance Analysis of Fault Prediction Models in PLC-Based AS/RS

Study Type	Data Modality	Model Used	Accuracy (%)	Sensitivity (%)	Limitations
Experimental Study	Sensor Data (Vibration, Temperature)	Random Forest (RF)	92	90	Requires large dataset, limited real-time testing
Experimental Study	PLC + IoT Data	Support Vector Machine (SVM)	89	87	Sensitive to parameter tuning
Simulation Study	Time-Series Data	LSTM (Deep Learning)	95	93	High computational cost
Case Study	Multi-Sensor Data	Artificial Neural Network (ANN)	91	88	Overfitting risk
Experimental Study	Industrial Big Data	CNN (Deep Learning)	94	92	Requires high training time
Simulation Study	PLC Logs + Sensor Data	K-Means + PCA	85	82	Lower accuracy for complex faults

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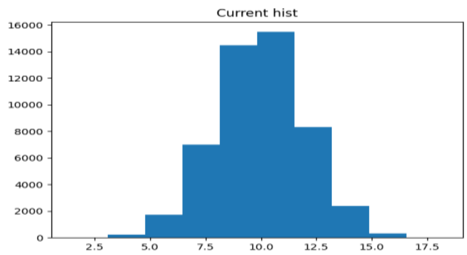
Case Study	Real-Time Streaming Data	Online Learning Model	90	89	Model drift issues
Experimental Study	IoT Sensor Data	Hybrid ML Model	93	91	Complex implementation
Simulation Study	Multi-Modal Data	Deep Hybrid Model	96	94	High computational complexity
Case Study	Edge + Sensor Data	Edge AI Model	92	90	Hardware dependency

RESEARCH GAP IDENTIFICATION

Despite significant advancements in fault prediction techniques for industrial automation systems, several critical research gaps remain, particularly in the context of PLC-based Automatic Storage and Retrieval Systems (AS/RS). Most existing studies focus on general industrial fault prediction rather than addressing the specific operational characteristics and complexities of AS/RS environments. These systems involve tightly integrated mechanical, electrical, and control components operating in real time, which require specialized predictive frameworks. However, many current approaches rely on traditional rule-based methods or standalone machine learning models that fail to capture complex system interactions and dynamic behaviors effectively [Pooya Sajjadi et al., 2025] Another major research gap lies in data availability and quality. Machine learning models require large volumes of labeled data for accurate training, but in real industrial environments, fault data is often limited, imbalanced, or noisy. This significantly affects the performance and generalization capability of predictive models. Additionally, most existing research does not adequately address the integration of multi-source data from PLCs, sensors, and communication systems, which is essential for developing robust fault prediction frameworks [Andrea Ferrari et al., 2025] Real-time implementation of fault prediction systems remains another significant challenge. Many studies validate their models using offline datasets or simulation environments, with limited consideration for real-time deployment in industrial settings. Issues such as latency, computational complexity, and compatibility with existing PLC architectures are often overlooked. Furthermore, the lack of edge computing and real-time data processing frameworks restricts the practical applicability of these models in dynamic environments such as AS/RS [Julien Chapelin et al., 2025] Another important gap is the lack of interpretability and transparency in advanced machine learning models. Deep learning techniques, although highly accurate, often function as “black-box” systems, making it difficult for operators to understand and trust their predictions. This limitation reduces their adoption in industrial applications where explainability is crucial for decision-making. Therefore, there is a growing need to integrate Explainable Artificial Intelligence (XAI) techniques into fault prediction frameworks [Junyu Guo et al., 2024] In addition, security and privacy concerns associated with data-driven industrial systems are not sufficiently addressed. With the increasing use of IoT and cloud-based platforms, industrial data becomes vulnerable to cyber threats. Very few studies explore secure and privacy-preserving approaches such as federated learning, which enables decentralized model training without sharing sensitive data, thereby enhancing data security [Gnana Swathika et al., 2024] Finally, there is a lack of comprehensive hybrid frameworks that combine traditional engineering knowledge with advanced data-driven techniques. Most existing approaches focus on individual models rather than developing integrated systems capable of adapting to varying operational conditions. Future research should focus on designing scalable, real-time, interpretable, and secure fault prediction frameworks specifically tailored for PLC-based AS/RS systems to bridge these gaps and improve system reliability and efficiency [Sen Yang et al., 2025]

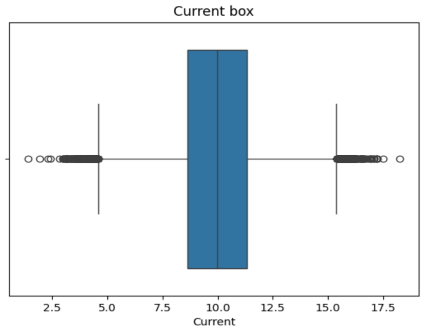
RESULTS AND DISCUSSION

Data Analysis and Interpretation



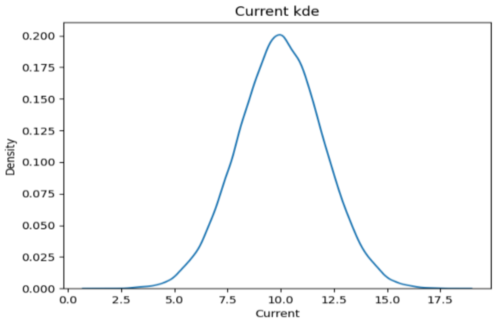
Graph1: Current Hist

The image shows a histogram of current values, illustrating how frequently different current ranges occur in the dataset. Most values are concentrated around the mid-range (approximately 9–11 units), indicating this is the most common current level. The distribution appears roughly bell-shaped, suggesting the current values follow a near-normal distribution.



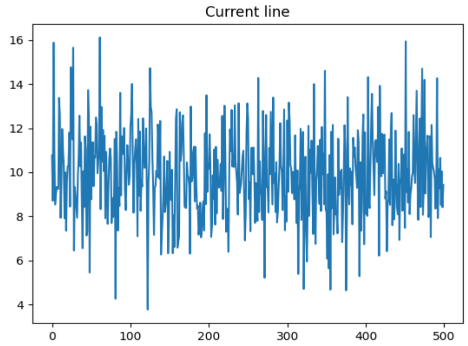
Graph 2: Current box

The image shows a box plot of current values, which summarizes the distribution using the median, quartiles, and potential outliers. The median current value is around 10 units, with most data points falling between approximately 8 and 12 units. Several outliers are visible on both the lower and higher ends, indicating some unusually low and high current readings.



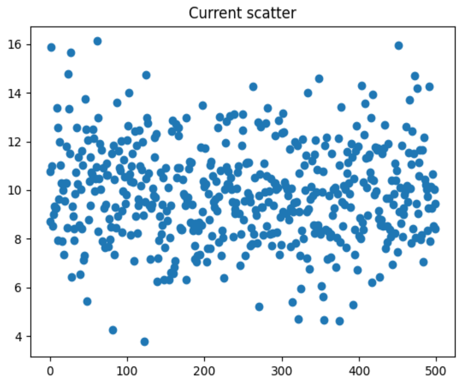
Graph 3: Current Kde

The image shows a Kernel Density Estimation (KDE) plot of current values, representing the smooth probability distribution of the data. The peak occurs around 10 units, indicating that this is the most common current value in the dataset. The curve gradually decreases on both sides, suggesting a near-normal distribution of current readings.



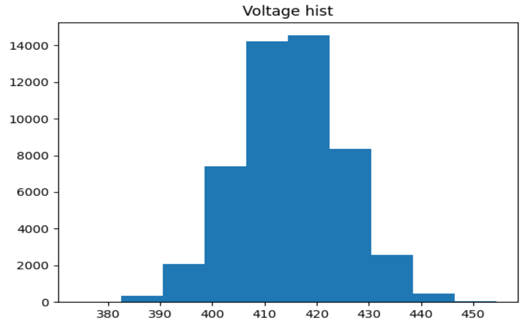
Graph 4: Current Line

The image shows a line plot of current values over multiple observations. The current fluctuates around an average value of approximately 9–11 units, with several peaks and dips throughout the sequence. This indicates natural variability in the current measurements over time or samples.



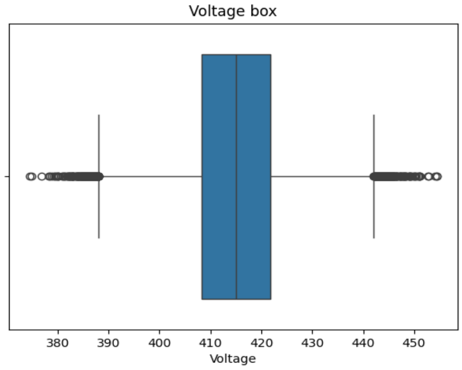
Graph 5: Current Scatter

The image shows a scatter plot of current values across different observations. The points are widely distributed, with most values concentrated between 8 and 12 units. This pattern indicates random variation in current measurements without a strong visible trend.



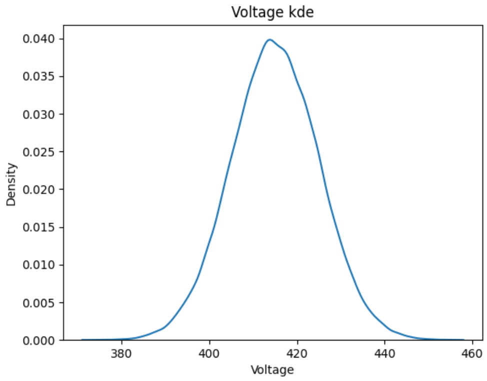
Graph 6: Voltage Hist

The image shows a histogram of voltage values, illustrating how frequently different voltage ranges occur in the dataset. Most voltage readings are concentrated around 410–420 units, indicating the typical operating range. The distribution appears roughly normal, with fewer values at the lower and higher voltage extremes.



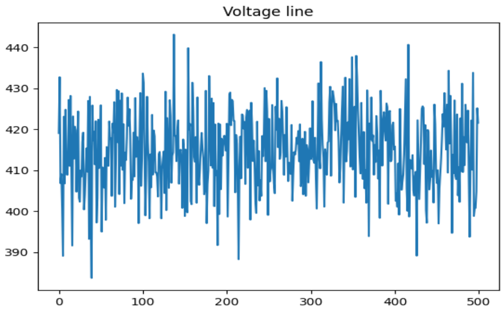
Graph 7: Voltage Box

The image shows a box plot of voltage values, summarizing the distribution using the median, quartiles, and outliers. The median voltage is around 415 units, with most values falling between approximately 405 and 425 units. Several outliers appear on both lower and higher ends, indicating occasional abnormal voltage readings.



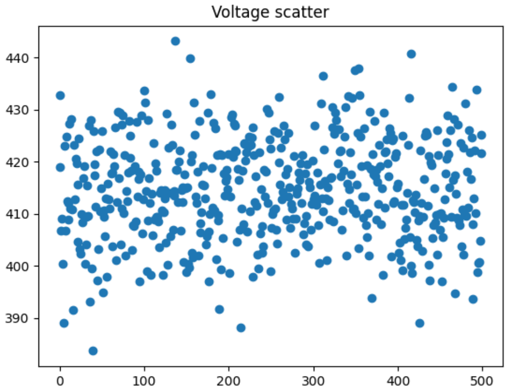
Graph 8: Voltage Kde

The image shows a Kernel Density Estimation (KDE) plot of voltage values, representing the smooth probability distribution of the data. The peak of the curve occurs around 415 units, indicating the most common voltage range. The symmetric shape of the curve suggests a near-normal distribution of voltage measurements.



Graph 9: Voltage line

The image shows a line plot of voltage values across multiple observations. The voltage fluctuates around an average range of 410–420 units, with occasional peaks and drops. This pattern indicates normal variation in voltage measurements over time or samples.



Graph 10: Voltage Scatter

The image shows a scatter plot of voltage values across different observations. Most data points are clustered between 400 and 430 units, indicating the common operating voltage range. The scattered pattern suggests random fluctuations in voltage without a clear trend over the observations.

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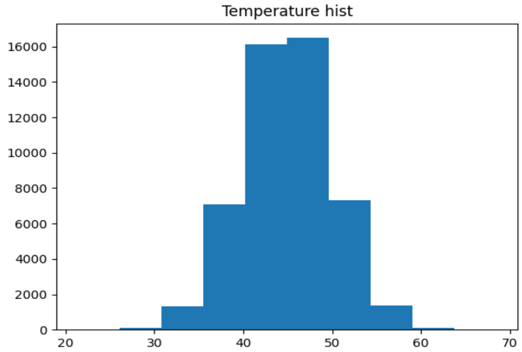
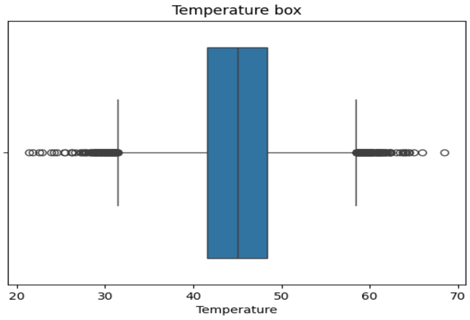


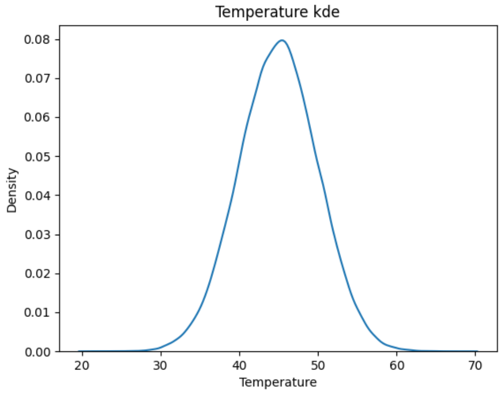
Graph 11: Temperature hist

The image shows a histogram of temperature values, illustrating how frequently different temperature ranges occur in the dataset. Most temperature readings are concentrated around 40–50 units, indicating the typical operating range. The distribution appears approximately normal, with fewer readings at very low and very high temperatures.



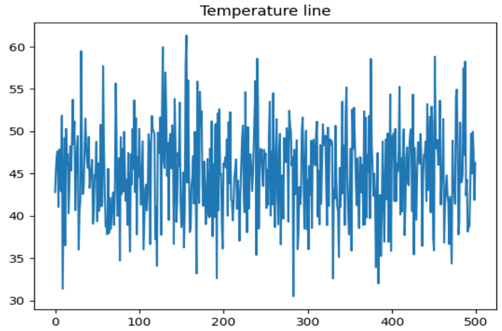
Graph 12: Temperature box

The image shows a box plot of temperature values, summarizing the distribution using the median, quartiles, and outliers. The median temperature is around 45 units, with most values lying between 40 and 50 units. Several outliers appear on both lower and higher sides, indicating occasional unusually low or high temperature readings.



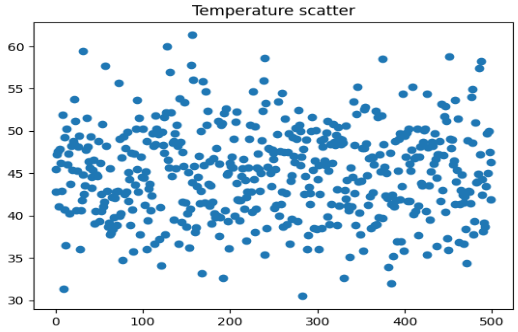
Graph 13: Temperature box

The image shows a Kernel Density Estimation (KDE) plot of temperature values, representing the smooth probability distribution of the data. The peak occurs around 45 units, indicating the most common temperature range. The symmetric curve suggests a near-normal distribution of temperature measurements.



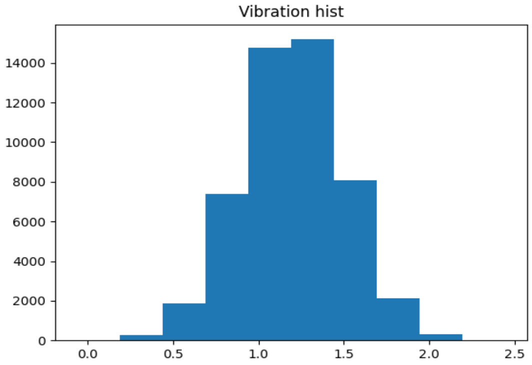
Graph 14: Temperature line

The image shows a line plot of temperature values across multiple observations. The temperature fluctuates around an average range of 40–50 units, with several peaks and drops. This pattern indicates normal variation in temperature measurements over time or across samples.



Graph 15: Temperature Scatter

The image shows a scatter plot of temperature values across different observations. Most data points are clustered between 40 and 50 units, indicating the common operating temperature range. The scattered pattern suggests random fluctuations in temperature without a clear trend over the observations.



Graph 16: Vibration hist

The image shows a histogram of vibration values, representing how frequently different vibration levels occur in the dataset. Most values are concentrated around 1.0–1.5 units, indicating the typical vibration range. The distribution appears approximately normal, with fewer readings at very low and very high vibration levels.

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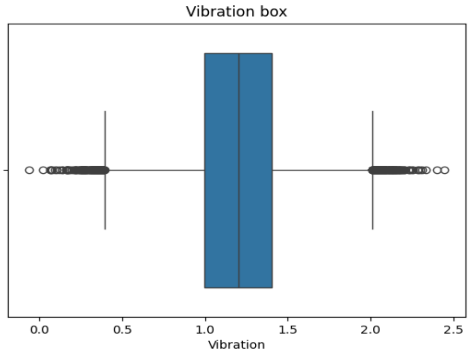
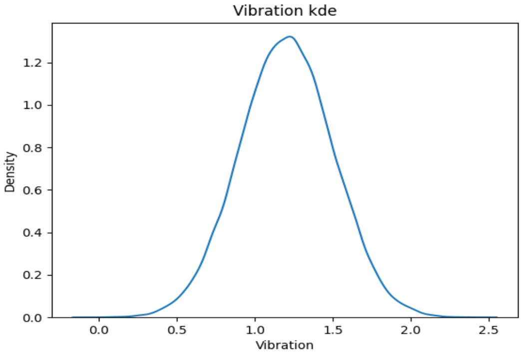


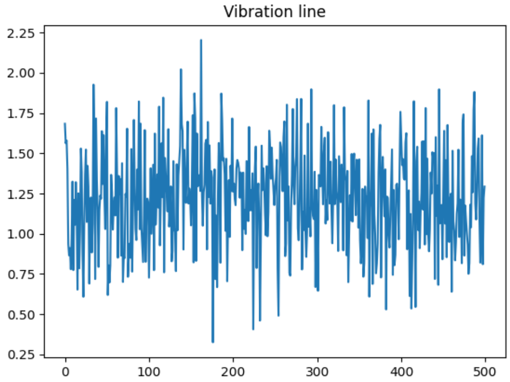
Graph 17: Vibration box

The image shows a box plot of vibration values, summarizing the distribution using the median, quartiles, and outliers. The median vibration is around 1.2 units, with most values lying between 1.0 and 1.4 units. Some outliers appear on both lower and higher sides, indicating occasional unusually low or high vibration readings.



Graph 18: Vibration kde

The image shows a Kernel Density Estimation (KDE) plot of vibration values, representing the smooth probability distribution of the data. The peak occurs around 1.2 units, indicating the most common vibration level. The bell-shaped curve suggests a near-normal distribution of vibration measurements.



Graph 19: Vibration line

The image shows a line plot of vibration values across multiple observations. The vibration levels fluctuate around an average range of 1.0–1.4 units, with several peaks and dips. This pattern indicates normal variations in vibration measurements over time or across samples.

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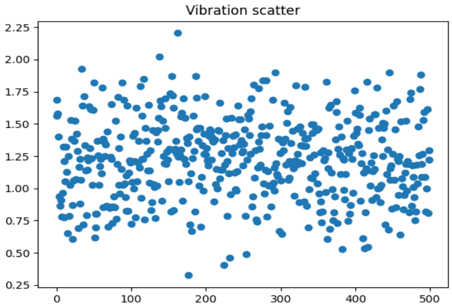
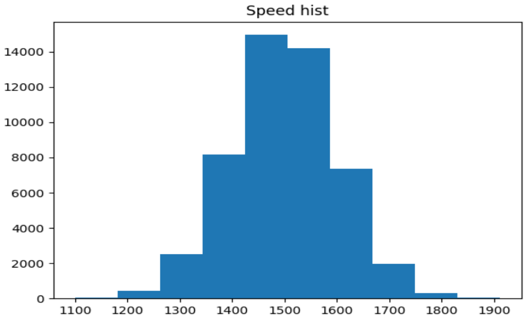


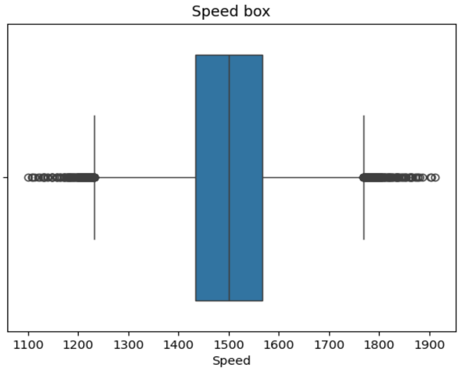
Graph 20: Vibration scatter

The image shows a scatter plot of vibration values across different observations. Most data points are clustered between 1.0 and 1.5 units, indicating the common vibration range. The scattered distribution suggests random fluctuations in vibration levels without a clear trend over the observations.



Graph 21: Speed hist

The image shows a histogram of speed values, representing how frequently different speed ranges occur in the dataset. Most values are concentrated around 1400–1600 units, indicating the typical operating speed. The distribution appears approximately normal, with fewer readings at very low and very highspeed levels.



Graph 22: Speed box

The image shows a box plot of speed values, summarizing the distribution using the median, quartiles, and outliers. The median speed is around 1500 units, with most values lying between 1400 and 1600 units. Some outliers appear on both lower and higher sides, indicating occasional unusually low or high speed readings.

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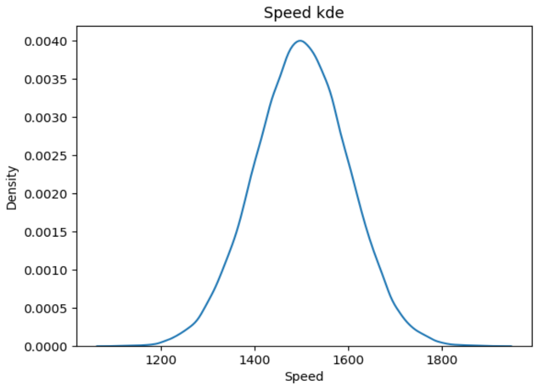
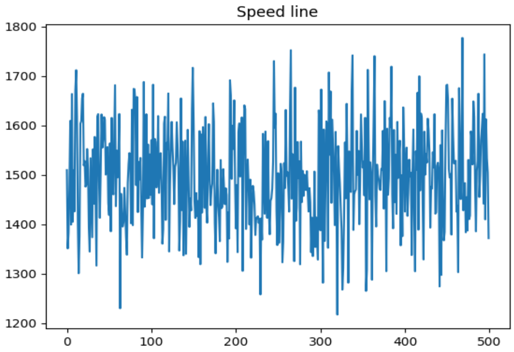


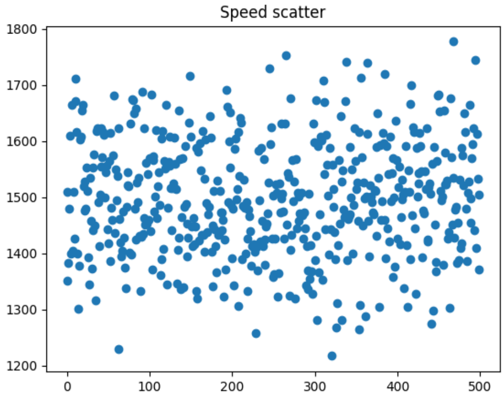
Graph 23: Speed kde

The image shows a Kernel Density Estimation (KDE) plot of speed values, representing the smooth probability distribution of the data. The peak occurs around 1500 units, indicating the most common operating speed. The bell-shaped curve suggests a near-normal distribution of speed measurements.



Graph 24: Speed line

The image shows a line plot of speed values across multiple observations. The speed fluctuates around an average range of 1400–1600 units, with several peaks and drops. This pattern indicates normal variations in speed measurements.



Graph 25: Speed scatter

The image shows a scatter plot of speed values across different observations. Most data points are clustered between 1400 and 1600 units, indicating the common operating speed range. The scattered pattern suggests random variations in speed without a clear trend over the observations.

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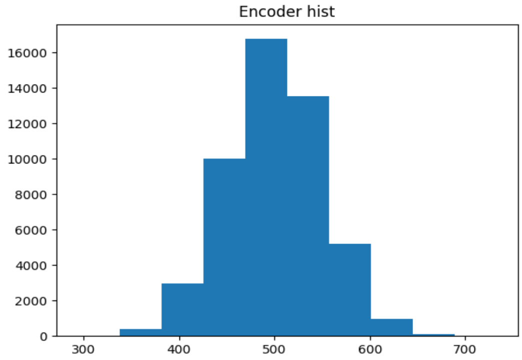
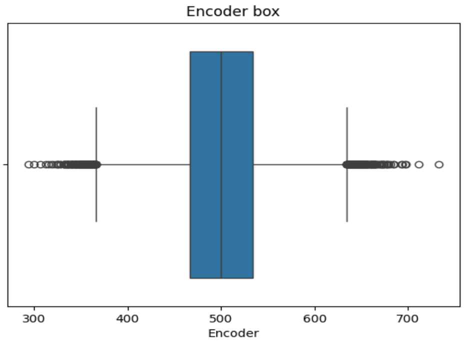


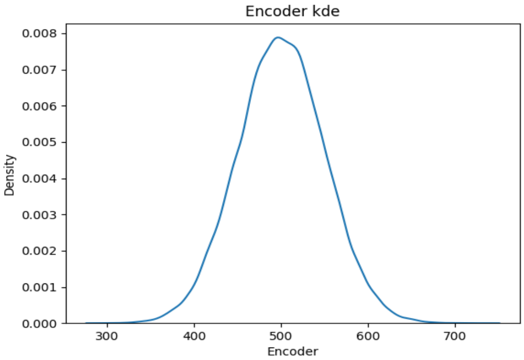
Graph 26: Encoder Hist

The image shows a histogram of encoder values, representing how frequently different encoder readings occur in the dataset. Most values are concentrated around 480–520 units, indicating the typical encoder range. The distribution appears approximately normal, with fewer readings at very low and very high encoder values



Graph 27: Encoder box

The image shows a box plot of encoder values, summarizing the distribution using the median, quartiles, and outliers. The median encoder value is around 500 units, with most readings falling between 460 and 540 units. Several outliers are visible on both lower and higher sides, indicating occasional unusually low or high encoder readings.



Graph 28: Encoder Kde

The image shows a Kernel Density Estimation (KDE) plot of encoder values, representing the smooth probability distribution of the data. The peak occurs around 500 units, indicating the most common encoder reading. The bell-shaped curve suggests a near-normal distribution of encoder measurements.

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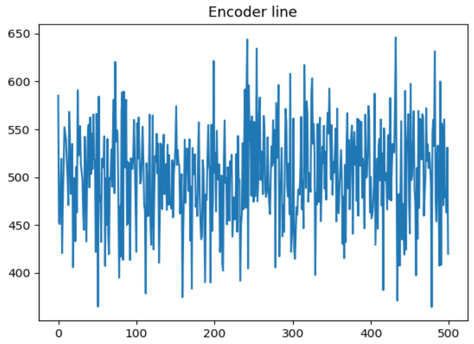
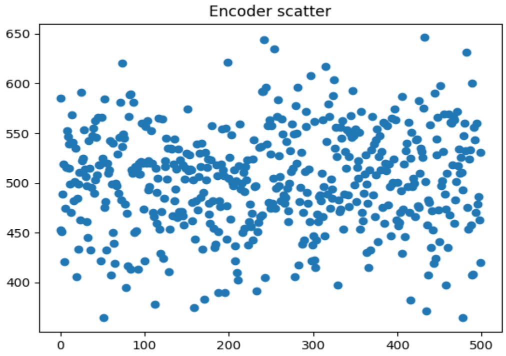


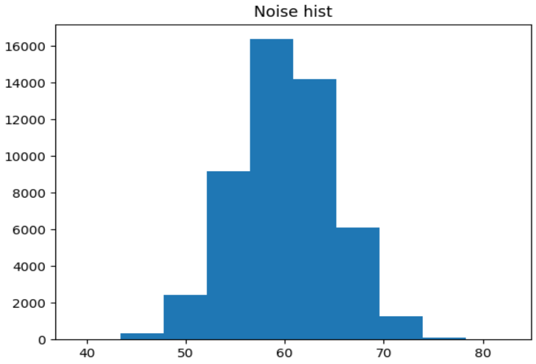
Graph 29: Encoder line

The image shows a line plot of encoder values across multiple observations. The encoder readings fluctuate around an average range of 480–520 units, with several peaks and drops. This pattern indicates normal variations in encoder measurements over time or across samples.



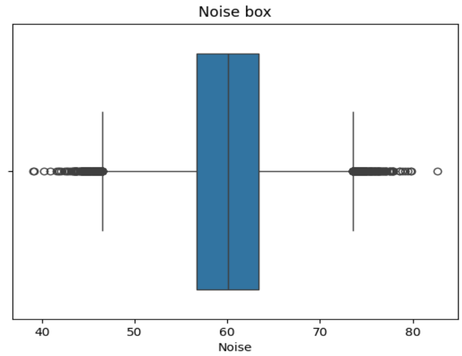
Graph 30: Encoder Scatter

The image shows a scatter plot of encoder values across different observations. Most data points are clustered between 480 and 540 units, indicating the common encoder reading range. The scattered distribution suggests random fluctuations in encoder values without a clear trend over the observations.



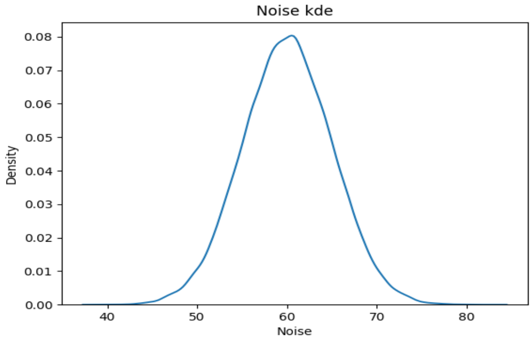
Graph 31: Noise hist

The image shows a histogram of noise values, illustrating how frequently different noise levels occur in the dataset. Most values are concentrated around 55–65 units, indicating the typical noise range. The distribution appears approximately normal, with fewer readings at very low and very high noise levels.



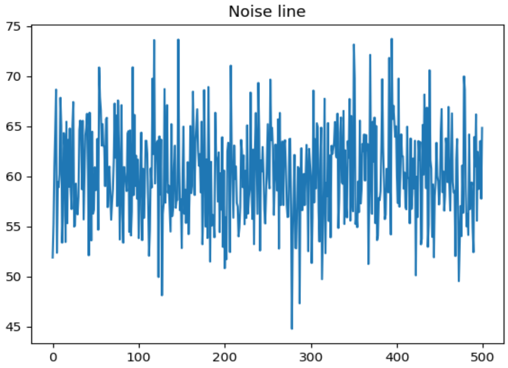
Graph 32: Noise box

The image shows a box plot of noise values, summarizing the distribution using the median, quartiles, and outliers. The median noise level is around 60 units, with most values lying between 55 and 65 units. Some outliers appear on both lower and higher sides, indicating occasional unusually low or high noise readings.



Graph 33: Noise kde

The image shows a Kernel Density Estimation (KDE) plot of noise values, representing the smooth probability distribution of the data. The peak occurs around 60 units, indicating the most common noise level in the dataset. The bell-shaped curve suggests a near-normal distribution of noise measurements.



Graph 34: Noise line

The image shows a line plot of noise values across multiple observations. The noise levels fluctuate around an average range of 55–65 units, with several peaks and dips. This pattern indicates normal variations in noise measurements over time or across samples.

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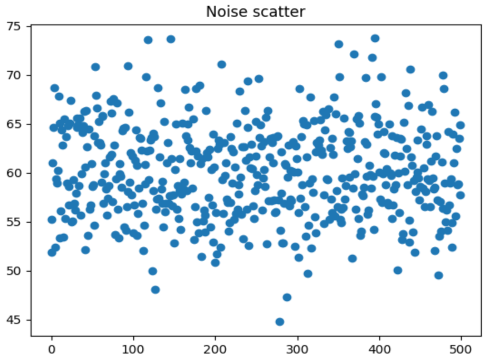
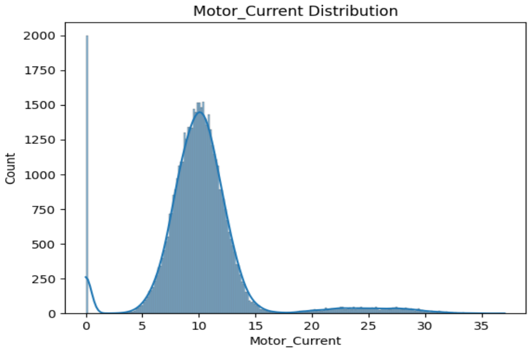


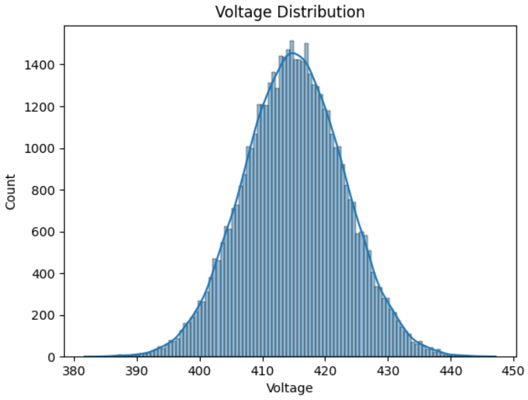
Graph 35: Noise scatter

The image shows a scatter plot of noise values across different observations. Most data points are clustered between 55 and 65 units, indicating the typical noise level range. The scattered pattern suggests random fluctuations in noise measurements without a clear trend over the observations.



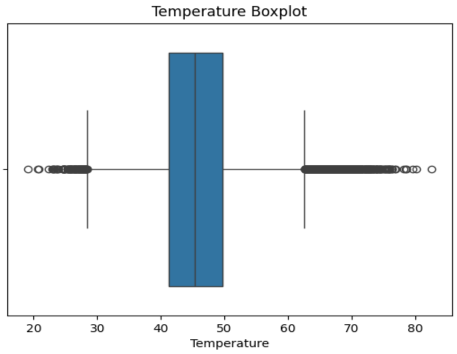
Graph 36: Motor current distribution

The image shows the distribution of motor current values using a histogram with a density curve. Most motor current readings are concentrated around 8–12 units, indicating the normal operating range of the motor. A small spread toward higher values suggests occasional higher current levels or possible abnormal operating conditions.



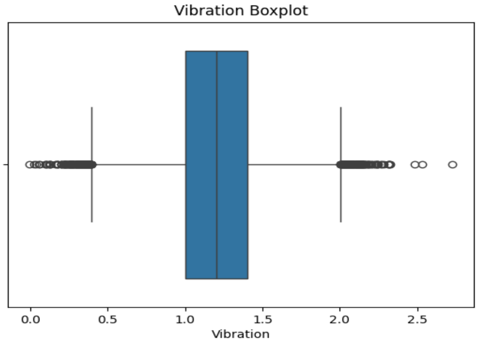
Graph 37: Voltage distribution

The image shows the distribution of voltage values using a histogram with a smooth density curve. Most voltage readings are concentrated around 410–420 units, indicating the typical operating voltage range. The bell-shaped curve suggests a normal distribution of voltage measurements.



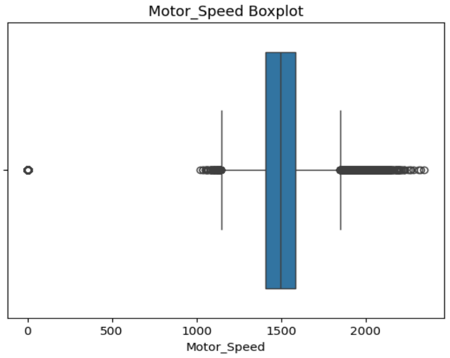
Graph 38: Temperature Boxplot

The image shows a box plot of temperature values, highlighting the median, quartiles, and outliers in the dataset. The median temperature is around 45–47 units, with most values distributed between 40 and 50 units. Several outliers appear on both lower and higher sides, indicating occasional unusually low or high temperature readings.



Graph 39: Vibration boxplot

The image shows a box plot of vibration values, illustrating the median, quartiles, and potential outliers in the dataset. The median vibration level is around 1.2 units, with most values distributed between 1.0 and 1.4 units. Some outliers are visible on both lower and higher sides, indicating occasional abnormal vibration readings.



Graph 40: Motor Speed Boxplot

The image shows a box plot of motor speed values, highlighting the median, quartiles, and outliers in the dataset. The median motor speed is around 1500 units, with most values lying between 1400 and 1600 units. Some outliers appear on both lower and higher sides, indicating occasional unusually low or high motor speed readings.

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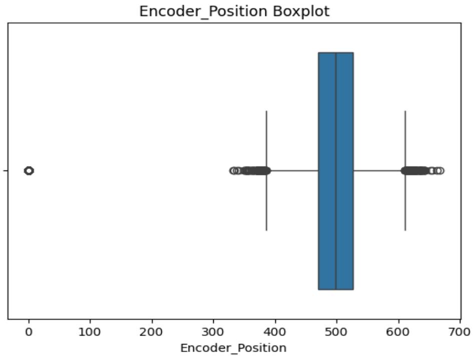
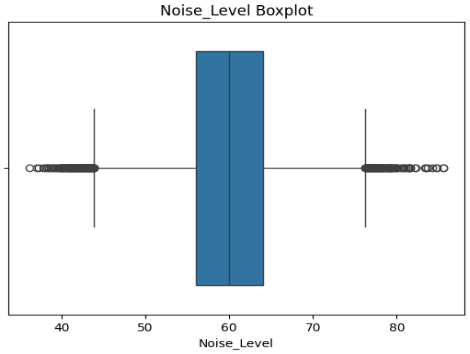


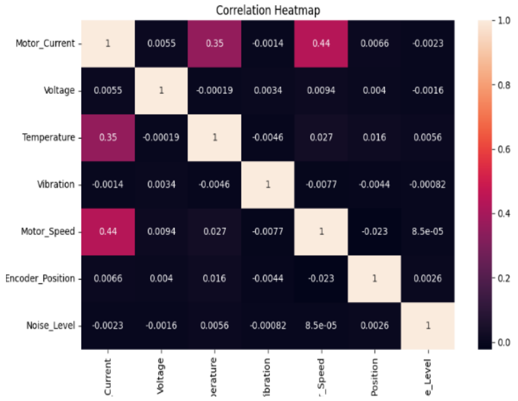
Graph 41: Encoder Position Boxplot

The image shows a box plot of encoder position values, highlighting the median, quartiles, and outliers in the dataset. The median encoder position is around 500 units, with most values lying between 470 and 530 units. Some outliers appear on both lower and higher sides, indicating occasional unusual encoder position readings.



Graph 42: Noise Level Boxplot

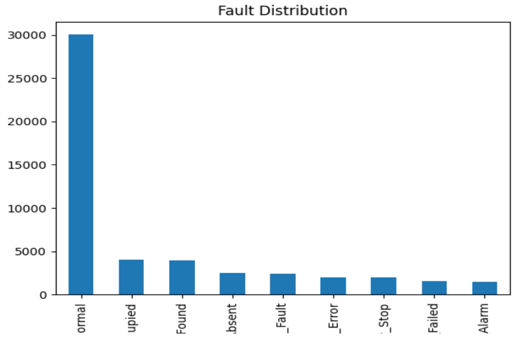
The image shows a box plot of noise level values, highlighting the median, quartiles, and potential outliers in the dataset. The median noise level is around 60 units, with most values distributed between 55 and 65 units. Several outliers appear on both lower and higher sides, indicating occasional unusually low or high noise readings.



	Current	Voltage	erature	ibration	_Speed	Position	e_Level
Motor_Current	1	0.0055	0.35	-0.0014	0.44	0.0066	-0.0023
Voltage	0.0055	1	-0.00019	0.0034	0.0094	0.004	-0.0016
Temperature	0.35	-0.00019	1	-0.0046	0.027	0.016	0.0056
Vibration	-0.0014	0.0034	-0.0046	1	-0.0077	-0.0044	-0.00082
Motor_Speed	0.44	0.0094	0.027	-0.0077	1	-0.023	8.5e-05
Encoder_Position	0.0066	0.004	0.016	-0.0044	-0.023	1	0.0026
Noise_Level	-0.0023	-0.0016	0.0056	-0.00082	8.5e-05	0.0026	1

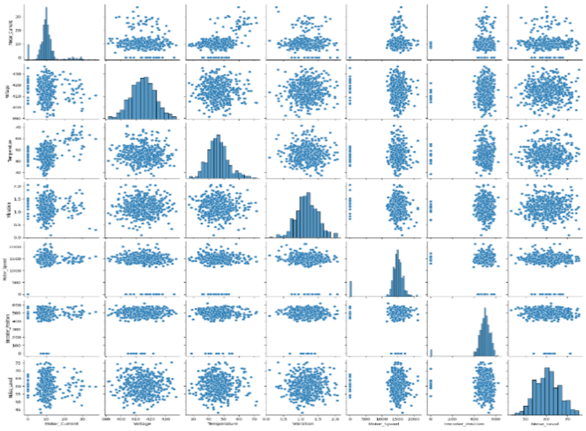
Graph 43: Correlation Heatmap

The image shows a correlation heatmap of different motor parameters, including current, voltage, temperature, vibration, speed, encoder position, and noise level. Most variables have very weak or near-zero correlations, indicating they operate largely independently.

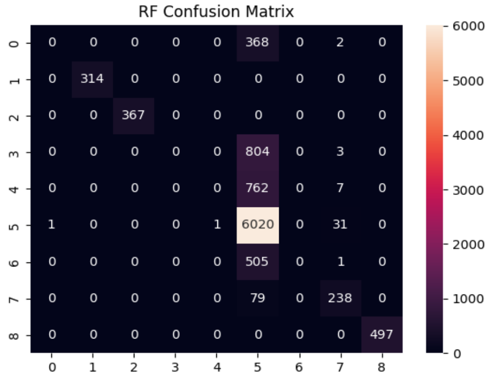


Graph 44: Fault Distribution

The image shows a bar chart representing the distribution of different fault conditions in the system. The Normal condition has the highest count, indicating most system operations occur without faults. Other categories such as Stuck, Imbalance, Fault, Error, Stop, Failed, and Alarm appear with significantly lower frequencies.



Graph 45: Sample Image



Graph 46: Rf Confusion Matrix

The image shows the confusion matrix of a Random Forest (RF) classification model, illustrating how well the model predicts different fault classes. The diagonal values represent correct predictions, while off-diagonal values indicate misclassifications between classes. Most predictions appear concentrated along the diagonal, suggesting the model performs well in identifying the correct fault categories.

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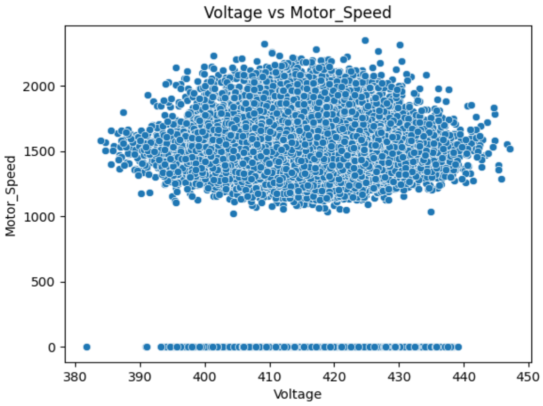
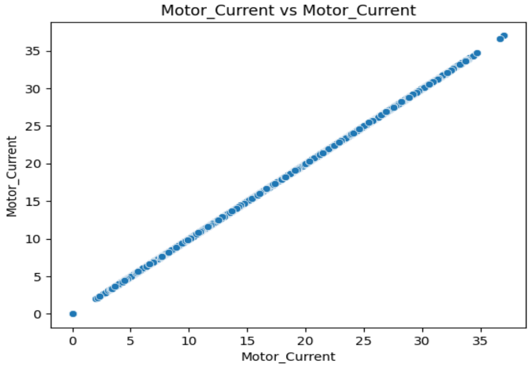


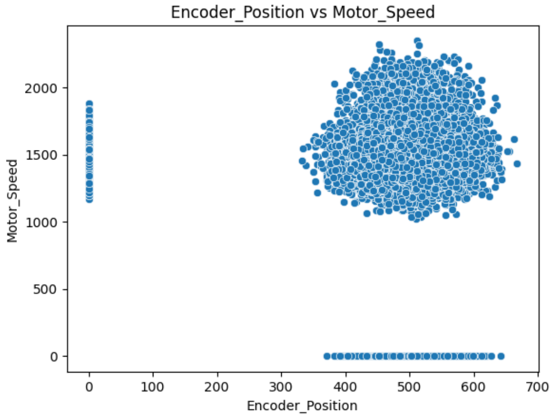
Graph 47: Voitage vs motor speed

The image shows a scatter plot of voltage versus motor speed, illustrating the relationship between these two parameters. Most data points cluster between 1400 and 2000 motor speed units while voltage ranges from 390 to 440 units.



Graph 48: Motor current vs motor current

The image shows a scatter plot comparing motor current with itself. All points lie on a perfect diagonal line, indicating a perfect positive correlation (correlation = 1). This occurs because the same variable is plotted on both axes, so every value matches exactly.



Graph 49: Encoder position vs motor speed

The image shows a scatter plot of encoder position versus motor speed. Most data points cluster between encoder positions of 400–600 units and motor speeds of 1200–2000 units, representing normal operating conditions. The

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spread of points indicates no strong linear relationship between encoder position and motor speed, with some points near zero suggesting possible idle or stopped states.

Dataset statistics

Table 1: Dataset statistics

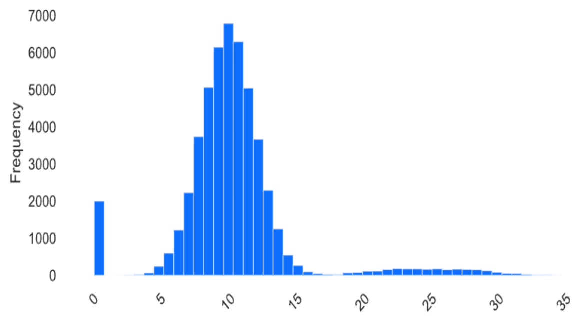
Number of variables	8
Number of observations	50000
Missing cells	0
Missing cells (%)	0.0%
Duplicate rows	0
Duplicate rows (%)	0.0%
Total size in memory	7.4 MiB
Average record size in memory	155.6 B
Numeric (Variable types)	7
Categorical	1

Table 2: Histogram with fixed size bins (bins=50)

Distinct	2394	Minimum	0
Distinct (%)	4.8%	Maximum	37.01
Missing	0	Zeros	1998
Missing (%)	0.0%	Zeros (%)	4.0%
Infinite	0	Negative	0
Infinite (%)	0.0%	Negative (%)	0.0%
Mean	10.325074	Memory size	390.8 KiB

Table 3: Quantile statistics & Descriptive statistics

Minimum	0	Standard deviation	4.3514232
5-th percentile	5.46	Coefficient of variation (CV)	0.42144233
Q1	8.51	Kurtosis	6.8339358
median	10.03	Mean	10.325074
Q3	11.53	Median Absolute Deviation (MAD)	1.51
95-th percentile	15.781	Skewness	1.5874349
Maximum	37.01	Sum	516253.69
Range	37.01	Variance	18.934884
Interquartile range (IQR)	3.02	Monotonicity	Not monotonic



Graph 50: Histogram with fixed size bins (bins=50)

The image shows a histogram with 50 fixed-size bins representing the distribution of values between approximately 0 and 35. Most of the data is concentrated around 8 to 12, where the frequency reaches its peak. A few values appear at the lower and higher ends, indicating the presence of outliers or less frequent observations.

Table 4: Histogram with fixed size bins (bins=50)

Distinct	4358	Minimum	381.63
Distinct (%)	8.7%	Maximum	447.2
Missing	0	Zeros	0
Missing (%)	0.0%	Zeros (%)	0.0%
Infinite	0	Negative	0
Infinite (%)	0.0%	Negative (%)	0.0%
Mean	415.0343	Memory size	390.8 KiB

Table 5: Quantile statistics & Descriptive statistics

Minimum	381.63	Standard deviation	8.0080081
5-th percentile	401.9395	Coefficient of variation (CV)	0.01929481
Q1	409.6	Kurtosis	-0.0037233892
median	415.02	Mean	415.0343
Q3	420.45	Median Absolute Deviation (MAD)	5.42
95-th percentile	428.19	Skewness	0.0039883568
Maximum	447.2	Sum	20751715
Range	65.57	Variance	64.128194
Interquartile range (IQR)	10.85	Monotonicity	Not monotonic

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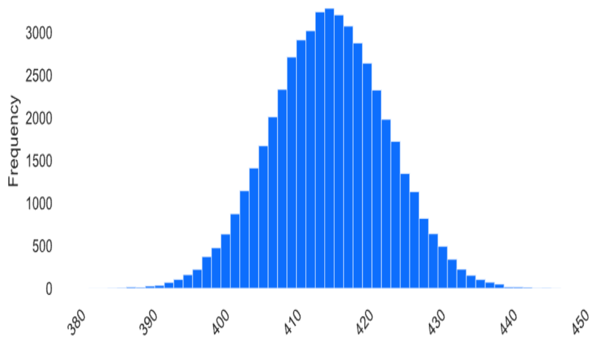

Graph 51: Histogram with fixed size bins (bins=50)

The image shows a histogram with 50 fixed-size bins displaying the distribution of values roughly between 380 and 450. The highest frequency occurs around 410–420, indicating most observations are concentrated in this range. The symmetric, bell-shaped curve suggests the data follows an approximately normal distribution.

Table 6: Histogram with fixed size bins (bins=50)

Distinct	3977	Minimum	19.05
Distinct (%)	8.0%	Maximum	82.6
Missing	0	Zeros	0
Missing (%)	0.0%	Zeros (%)	0.0%
Infinite	0	Negative	0
Infinite (%)	0.0%	Negative (%)	0.0%
Mean	45.742194	Memory size	390.8 KiB

Table 7: Quantile statistics & Descriptive statistics

Minimum	19.05	Standard deviation	6.7864873
5-th percentile	35.4	Coefficient of variation (CV)	0.14836383
Q1	41.2	Kurtosis	0.93801126
median	45.39	Mean	45.742194
Q3	49.76	Median Absolute Deviation (MAD)	4.28
95-th percentile	57.36	Skewness	0.48143515
Maximum	82.6	Sum	2287109.7
Range	63.55	Variance	46.05641
Interquartile range (IQR)	8.56	Monotonicity	Not monotonic

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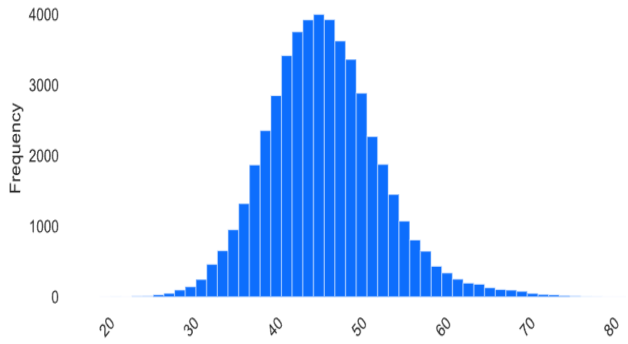


Graph 52: Histogram with fixed size bins (bins=50)

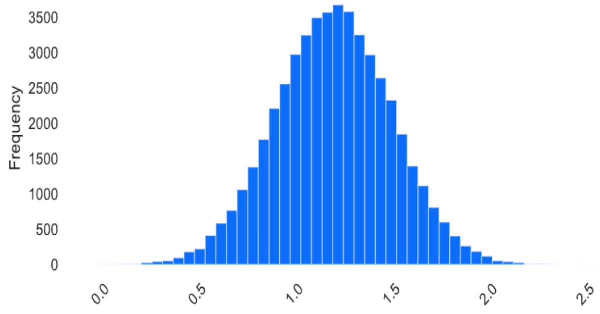
The image shows a histogram with 50 fixed-size bins illustrating the distribution of values between approximately 20 and 80. The frequency of observations peaks around 45–50, indicating that most data points are concentrated near this range. The bell-shaped pattern suggests the dataset follows an approximately normal distribution.

Table 8: Histogram with fixed size bins (bins=50)

Distinct	1840	Minimum	-0.01
Distinct (%)	3.7%	Maximum	2.73
Missing	0	Zeros	0
Missing (%)	0.0%	Zeros (%)	0.0%
Infinite	0	Negative	1
Infinite (%)	0.0%	Negative (%)	< 0.1%
Mean	1.199659	Memory size	390.8 KiB

Table 9: Quantile statistics & Descriptive statistics

Minimum	-0.01	Standard deviation	0.2989376
5-th percentile	0.708	Coefficient of variation (CV)	0.24918548
Q1	0.999	Kurtosis	0.01527625
median	1.2	Mean	1.199659
Q3	1.402	Median Absolute Deviation (MAD)	0.202
95-th percentile	1.69	Skewness	-0.0017326708
Maximum	2.73	Sum	59982.949
Range	2.74	Variance	0.089363688
Interquartile range (IQR)	0.403	Monotonicity	Not monotonic



Graph 53: Histogram with fixed size bins (bins=50)

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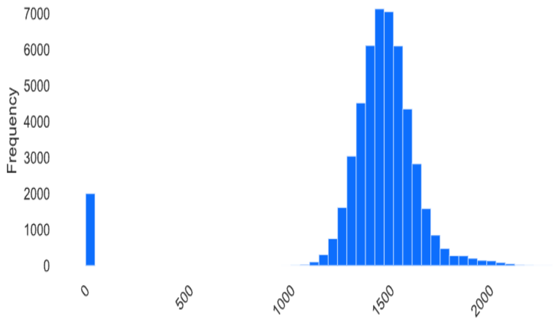
The image shows a histogram with 50 fixed-size bins representing the distribution of data values. The frequency increases gradually, reaches a peak around the center (approximately 1.1–1.3), and then decreases symmetrically. This bell-shaped pattern indicates that the data follows an approximately normal distribution, where most values are concentrated near the mean.

Table 10: Histogram with fixed size bins (bins=50)

Distinct	30381	Minimum	0
Distinct (%)	60.8%	Maximum	2348.17
Missing	0	Zeros	1998
Missing (%)	0.0%	Zeros (%)	4.0%
Infinite	0	Negative	0
Infinite (%)	0.0%	Negative (%)	0.0%
Mean	1452.9432	Memory size	390.8 KiB

Table 11: Quantile statistics & Descriptive statistics

Minimum	0	Standard deviation	326.34201
5-th percentile	1228.178	Coefficient of variation (CV)	0.22460755
Q1	1410.1875	Kurtosis	12.938703
median	1499.225	Mean	1452.9432
Q3	1586.66	Median Absolute Deviation (MAD)	88.225
95-th percentile	1737.933	Skewness	-3.3683392
Maximum	2348.17	Sum	72647161
Range	2348.17	Variance	106499.11
Interquartile range (IQR)	176.4725	Monotonicity	Not monotonic



Graph 54: Histogram with fixed size bins (bins=50)

The image shows a histogram with fixed-size bins (50 bins) representing the distribution of motor speed values. Most data points are concentrated around 1400–1600 units, forming a bell-shaped distribution. A small bar near 0 indicates a few idle or stopped motor conditions compared to the main operating range.

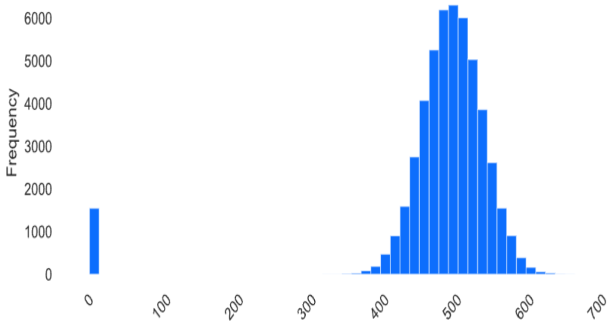
Table 12: Histogram with fixed size bins (bins=50)

Distinct	15745	Minimum	0
Distinct (%)	31.5%	Maximum	667.98

Missing	0	Zeros	1545
Missing (%)	0.0%	Zeros (%)	3.1%
Infinite	0	Negative	0
Infinite (%)	0.0%	Negative (%)	0.0%
Mean	484.70007	Memory size	390.8 KiB

Table 13: Quantile statistics & Descriptive statistics

Minimum	0	Standard deviation	95.090403
5-th percentile	417.439	Coefficient of variation (CV)	0.19618401
Q1	469.8675	Kurtosis	17.980671
median	498.535	Mean	484.70007
Q3	526.2725	Median Absolute Deviation (MAD)	28.185
95-th percentile	565.4315	Skewness	-4.005031
Maximum	667.98	Sum	24235004
Range	667.98	Variance	9042.1847
Interquartile range (IQR)	56.405	Monotonicity	Not monotonic



Graph 55: Histogram with fixed size bins (bins=50)

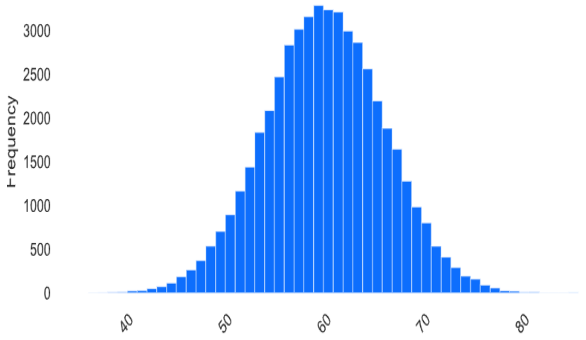
The image shows a histogram with fixed-size bins (50 bins) representing the distribution of encoder position values. Most data points are concentrated around 480–560 units, forming a bell-shaped distribution. A small bar near 0 indicates a few abnormal or idle readings compared to the main cluster.

Table 14: Histogram with fixed size bins (bins=50)

Distinct	3367	Minimum	36.1
Distinct (%)	6.7%	Maximum	85.6
Missing	0	Zeros	0
Missing (%)	0.0%	Zeros (%)	0.0%
Infinite	0	Negative	0
Infinite (%)	0.0%	Negative (%)	0.0%
Mean	60.009336	Memory size	390.8 KiB

Table 15: Quantile statistics & Descriptive statistics

Minimum	36.1	Standard deviation	5.9994648
5-th percentile	50.11	Coefficient of variation (CV)	0.099975523
Q1	55.98	Kurtosis	0.017831744
median	60	Mean	60.009336
Q3	64.07	Median Absolute Deviation (MAD)	4.05
95-th percentile	69.87	Skewness	0.0017035681
Maximum	85.6	Sum	3000466.8
Range	49.5	Variance	35.993577
Interquartile range (IQR)	8.09	Monotonicity	Not monotonic



Graph 56: Histogram with fixed size bins (bins=50)

The image shows a histogram with fixed-size bins (50 bins) representing the distribution of values in the dataset. Most data points are concentrated around 55–65 units, forming a bell-shaped curve. This indicates the data follows an approximately normal distribution with a central peak near 60.

Table 16: Length

Distinct	9	1st row	Normal
Distinct (%)	< 0.1%	2nd row	Normal
Missing	0	3rd row	Normal
Missing (%)	0.0%	4th row	Normal
Memory size	4.7 MiB	5th row	Normal

Table 17: characters and Unicode

Total characters	528316
Distinct characters	36
Distinct categories	1?
Distinct scripts	1?
Distinct blocks	1?

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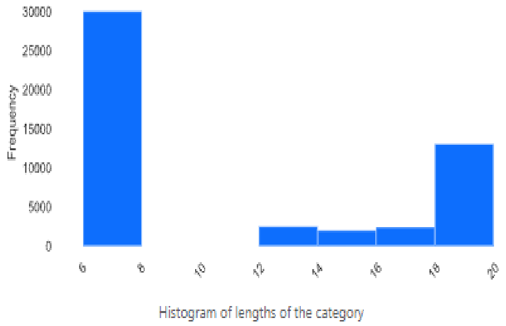
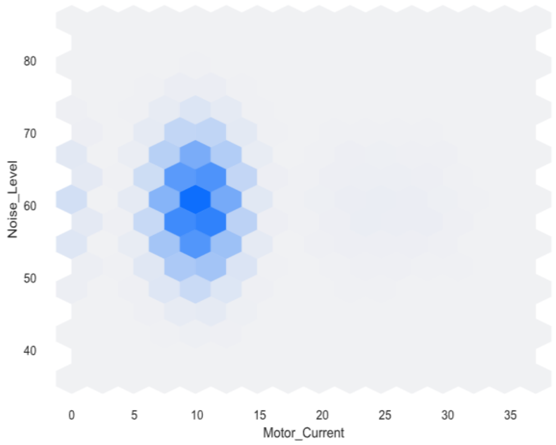
Unique (Unique)	0?
Unique (%)	0.0%



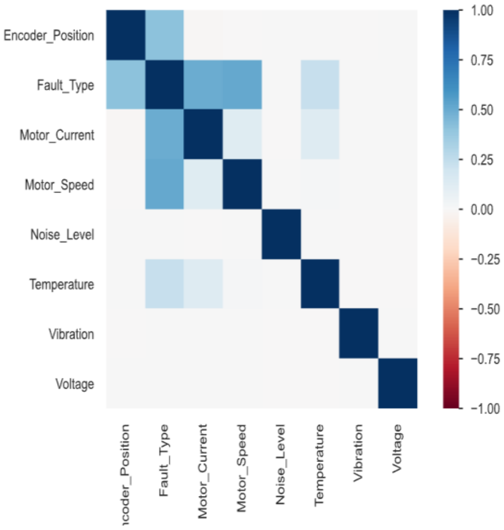
Graph 57: Histogram of lengths of the category

The image presents a histogram and category distribution of fault types in the dataset. The lower chart shows that the “Normal” category dominates with about 60.1% (30,046 samples), while other categories such as Front Rack Occupied, Material Not Found, Pallet Absent, and system faults appear in smaller proportions. This indicates that most system operations occur under normal conditions, with relatively fewer fault events.



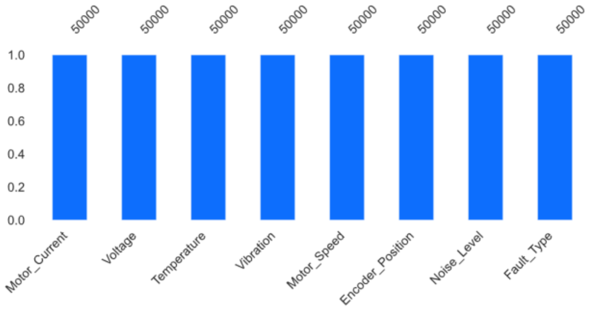
Graph 58: Interactions

The image shows a hexbin interaction plot between motor current and noise level, representing the density of data points. The darker hexagonal areas indicate higher concentrations of observations, mainly around motor current of 8–12 units and noise levels near 55–65 units. This suggests that most machine operations occur within this common operating range of current and noise.



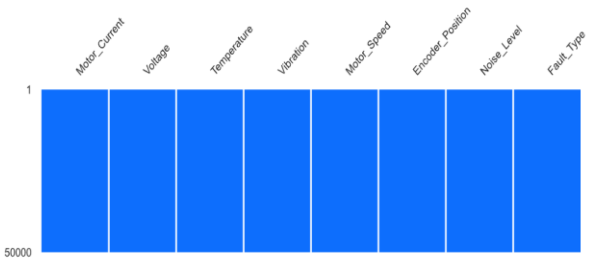
Graph 59: Correlations

The image shows a correlation heatmap of different machine parameters, including encoder position, motor current, motor speed, temperature, vibration, voltage, and noise level. The diagonal values represent perfect correlation (1.0) of each variable with itself, while the lighter colors indicate weak to moderate relationships between some variables. Overall, most parameters show low correlation with each other, suggesting they operate largely independently.



Graph 60: Missing values Count

The image shows a bar chart representing the count of missing values for each dataset feature. All variables such as motor current, voltage, temperature, vibration, motor speed, encoder position, noise level, and fault type show a full count of 50,000 entries. This indicates that no missing values are present and the dataset is complete



Graph 61: Missing values Matrix

The image shows a missing values matrix for the dataset, visualizing the availability of data across all features. Each column represents variables such as motor current, voltage, temperature, vibration, motor speed, encoder

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position, noise level, and fault type. The fully filled columns indicate no missing values in the dataset, meaning the data is complete and ready for analysis.

CONCLUSION

This chapter presented a comprehensive review of fault prediction techniques in industrial systems with a particular focus on PLC-based Automatic Storage and Retrieval Systems (AS/RS). It highlighted the growing importance of data-driven approaches in modern industrial automation, driven by advancements in machine learning, IoT, and smart manufacturing technologies. Traditional fault detection methods, such as rule-based systems and preventive maintenance strategies, were found to be limited in their ability to handle complex and dynamic system behaviors, thereby emphasizing the need for intelligent predictive models. The chapter also examined various types of faults in AS/RS systems, including mechanical failures, electrical and PLC-related issues, and sensor or communication errors. These faults significantly impact system reliability, operational efficiency, and overall productivity. It was observed that effective fault prediction requires the integration of multi-source data and advanced analytical techniques to accurately capture system behavior and identify potential failures at an early stage.

Furthermore, machine learning techniques, including supervised, unsupervised, and deep learning models, were discussed as powerful tools for improving fault detection accuracy and enabling predictive maintenance. Data-driven approaches allow continuous monitoring and analysis of system performance, which helps in reducing downtime and maintenance costs. However, several challenges were identified, such as data quality issues, lack of labeled datasets, computational complexity, and difficulties in real-time implementation. The comparative analysis of existing methods revealed that while machine learning-based approaches offer higher accuracy and adaptability compared to traditional techniques, they also require significant computational resources and expertise. Additionally, issues related to model interpretability, system integration, and data security remain major concerns in practical applications. Overall, the review indicates that although considerable progress has been made in fault prediction technologies, there is still a need for developing robust, scalable, and real-time frameworks specifically designed for PLC-based AS/RS systems. These frameworks should focus on efficient data integration, improved model transparency, and seamless deployment in industrial environments. The insights gained from this chapter provide a strong foundation for the proposed methodology and highlight the importance of advanced machine learning techniques in enhancing system reliability and operational efficiency.

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