PREDICTIVE MAINTENANCE AND TIME SERIES FORECASTING FOR INDUSTRIAL EQUIPMENT HEALTH MONITORING AT PT.XYZ

THESIS PROPOSAL

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APPROVAL SHEET

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CHAPTER I. INTRODUCTION

1.1 Background

In the dynamic landscape of industrial operations and manufacturing, the proper management and maintenance of equipment are paramount to ensure efficiency, productivity, and cost-effectiveness. The ability to predict equipment failures accurately and manage predictive maintenance plans efficiently is a significant concern for industries across the globe. Breakdowns and unscheduled downtime can lead to substantial financial losses and reduced productivity, emphasizing the importance of adopting advanced strategies for predictive maintenance.

In the dynamic landscape of industrial operations and manufacturing, industrial equipment health emphasizes a growing reliance on advanced technologies such as IoT (Internet of Things), AI (Artificial Intelligence), and data analytics for real-time monitoring and predictive maintenance (Çınar et al., 2020). Industries are increasingly recognizing the significance of continuously monitoring the health of industrial equipment to ensure operational efficiency, minimize downtime, and prevent costly breakdowns. This shift from reactive to proactive maintenance strategies is driven by the imperative to enhance overall productivity, reduce operational costs, and improve workplace safety. Comprehensive industrial equipment health monitoring not only prolongs the lifespan of machinery but also facilitates data-driven decision-making, enabling companies to optimize resource allocation and stay competitive in an ever-evolving industrial landscape. The integration of Industry 4.0 principles, emphasizing connectivity and automation, further underscores the importance of caring about industrial equipment health as a strategic imperative for sustainable and efficient industrial operations. It plays an important role in the control of costs associated with operating large industrial equipment (Yucesan et al., 2021).

Traditionally, maintenance strategies have been primarily reactive or preventive, often leading to unnecessary maintenance activities and increased operational costs. Predictive Maintenance (PDM) stands as a more proactive approach, aiming to reduce downtime by forecasting equipment failures and scheduling maintenance activities precisely when needed. PDM relies on the collection of historical equipment data and the implementation of predictive modeling techniques, such as Time Series Forecasting, to anticipate failures.

Continuing from the previous research, various approaches and methods have been employed. In the way how to be expanding on previous research, the SG-FCM algorithm was applied, it aims to enhance equipment health status assessment precision through dynamic adaptation. However, notable weaknesses exist. The algorithm's reliance on a predetermined number of clusters (K) requires manual input, potentially limiting adaptability across datasets. Dependency on typical cases for health status recognizers may struggle with unforeseen degradation patterns. Clarity is needed on the algorithm's sensitivity to operating conditions, with recalibration specifics unspecified. Raising questions about generalizability. Lack of real-world implementation results and a comparative analysis with alternative methods compounds limitations. A more comprehensive exploration of fault prediction and residual life calculations is crucial for practical understanding of the SG-FCM algorithm (Zhou et al., 2019).

Despite its potential benefits, implementing PDM is not without its challenges. Equipment data can be vast and complex, and selecting the most suitable Time Series Forecasting model can be a daunting task. The effectiveness of predictive maintenance systems depends heavily on the accuracy and precision of the forecasting models in use.

Predictive maintenance is highly beneficial for monitoring the health of Industrial equipment, providing a proactive approach to identify potential issues before they result in equipment failure. By leveraging advanced analytics and machine learning algorithms, predictive maintenance can anticipate equipment failures, allowing for timely interventions like repairs or replacements. This predictive approach is instrumental in minimizing unplanned downtime, reducing maintenance costs, and extending the overall lifespan of industrial machinery, thereby contributing to more efficient and reliable operations. The implementation of a Prognostic and Health Management (PHM) system further solidifies this approach, offering a comprehensive solution for managing equipment health, including fault diagnosis and remaining useful life (RUL) estimation, especially in industrial contexts. The integration of the latest research in modern information technology and AI technology enhances the effectiveness of the PHM system, making Predictive Maintenance (PdM) crucial and integral component of this comprehensive approach to equipment health management (Zhang et al., 2019).

Time series forecasting is exceptionally advantageous for monitoring the health of industrial equipment by analyzing historical data patterns and predicting future conditions. This forecasting technique, rooted in key areas of academic research such as climate modeling, biological sciences, and medicine, as well as applications in commercial decision-making in retail and finance, enables early detection of anomalies and facilitates proactive maintenance measures to prevent potential equipment failures (Lim & Zohren, 2021). The predictive nature of time series forecasting not only allows for optimized scheduling of maintenance activities, leading to resource efficiency and cost savings but also aligns with the fundamental concept of time series—a set of measures collected at even intervals and ordered chronologically. Given this definition, it is challenging to find physical or chemical phenomena without variables evolving over time, making time series forecasting approaches applicable and fruitful across diverse scientific disciplines (Torres et al., 2021). This proactive approach not only minimizes downtime but also enhances operational efficiency by strategically directing maintenance efforts, thereby contributing to overall equipment reliability and longevity.

For trend analysis process, the auto regressive integrated moving average (ARIMA) model is used. The trend is analyzed, and failure can be predicted by using this model. The output from this model is used as raw features and fed to the principal component analysis (PCA) for generating the uncorrelated features. These PCA features are then used to train the prediction model. And thus, the final predictions are made. Fig. 1. Proposed Framework The rest of this paper is organized as follows. Section 2 briefly provides an overview of the related works in the field of trend analysis, failure prediction and predictive maintenance. Section 3 presents the overall architecture of the system and provides a detailed description of the same. Section 4 illustrates the results obtained and the performance evaluation of the model and Section 5 concludes the work by providing the future scope of the same. The main idea behind this is that first we predict values from the monitored variables using both fuzzy inference and ARIMA model. Then the comparison of these values can be done, and the difference is taken. If the difference is larger the threshold given, there are greater chances for failure to occur.Otherwise, the system can run well at that time. The major benefit of this method is that it can take into account discrete, continuous and fuzzy variables. Fig. 4. shows the methodology for the proposed system. The data stored in the database is taken for the analysis and for further prediction tasks. The basic concept behind this is: The time series data is taken to the ARIMA model for trend analysis. The predictions or predicted features from the ARIMA model is then fed to the PCA for the reduction of feature set with minimal correlation features. ARIMA model aims at using all the history of past fault events and then analyze it for forecasting or predicting the future failure. It is in the form of predictive features. These raw features are then converted to a reduced feature set of PCA features with minimal correlation among each other. These features are then used for maintenance prediction task. When a new time series data arrives of fault events and sensor values, it then extracts the features using ARIMA model and then PCA features are extracted. Support vector regression model is used for predicting the maintenance. ARIMA model helps in the analyzing the evolution of trend from the values provided. Principal component analysis is a technique used for dimensionality reduction of dataset from multiple sources.

In the pursuit of enhancing predictive accuracy within the domain of industrial equipment health monitoring, this research introduces a specialized ARIMA-based prediction method. Auto Regressive Integrated Moving Average (ARIMA) is a widely used time series forecasting algorithm in statistics and econometrics. It is designed to capture and model various components of time series data, including trend, seasonality, and noise. According to research by Francis & Mohan (2019), the advantages of employing the ARIMA method in this context lie in its capability to analyze trends, incorporate historical information for forecasting, predict maintenance needs, and handle different types of variables in a transportation system, ultimately contributing to the efficient and proactive management of the system's components. The additional research closely aligns with existing literature, systematically evaluating the efficacy of the ARIMA model in forecasting Daily Machine Performance Check (MPC) outcomes within the broader context of "Predictive Maintenance and Time Series Forecasting for Industrial Equipment Health Monitoring." The ARIMA model consistently yields precise predictions, substantiated by notably low values of Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE), establishing a robust correlation with actual MPC test results. Demonstrating adeptness in identifying warning stages, the model attains a consistently high average accuracy level that surpasses 85.00% in the majority of cases. In summation, the ARIMA model manifests a formidable predictive capacity for daily MPC outcomes within the realm of predictive maintenance and time series forecasting for industrial equipment health monitoring (Puyati et al., 2020). The primary strengths of the ARIMA forecasting approach are its straightforward application and easy interpretability. However, it is important to note that the method is susceptible to the impact of outliers in the data and does not explicitly address unknown noise. Consequently, while ARIMA is well-suited for short-term forecasting, caution is advised in interpreting results as they may be influenced by the presence of outliers and unaccounted-for noise (Perone, 2020). This comprehensive methodology not only aligns with the inherent benefits of the ARIMA algorithm but also ensures a sustainable framework for advancing industrial equipment health monitoring practices.

This thesis, "PREDICTIVE MAINTENANCE AND TIME SERIES FORECASTING FOR INDUSTRIAL HEALTH EQUIPMENT AT PT.XYZ" addresses the need for comprehensive evaluation and comparison of various Time Series Forecasting models in the context of predictive maintenance. Understanding the performance and suitability of different forecasting methods is crucial to determine the most effective approach for minimizing equipment downtime, reducing maintenance costs, and optimizing overall operational efficiency.

This thesis "PREDICTIVE MAINTENANCE AND TIME SERIES FORECASTING FOR INDUSTRIAL HEALTH EQUIPMENT AT PT.XYZ," strategically positions itself in alignment with the pivotal concept that the integration of predictive maintenance and time series analysis holds the potential to catalyze substantial improvements. Today, predictive maintenance stands as a linchpin in sustainable manufacturing and production systems, ushering in a digital iteration of machine maintenance (Achouch et al., 2022). The overarching purpose of this study seamlessly intertwines with the pursuit of solutions crucial for advancing the management of industrial health equipment. To achieve this objective, the research embarks on a comprehensive journey of evaluation and comparison, concentrating on a diverse array of Time Series Forecasting models within the dynamic context of predictive maintenance. This deliberate examination serves as a cornerstone, illuminating the nuanced performance and suitability of various forecasting methods. The ultimate goal is to discern and implement the most effective approach, not only for minimizing equipment downtime and reducing maintenance costs but also for fostering a sustainable enhancement of overall operational efficiency. In its entirety, this study represents a cohesive effort to bridge theoretical insights with practical applications, thereby contributing to a lasting and meaningful improvement in the realm of industrial health equipment management.

1.2 Problem Formulation

Based on the background that has been presented, the research problem can be formulated as follows:

1. How does improving the ARIMA-based prediction method enhance monitoring industrial equipment health?
2. How do the integration of time series forecasting techniques into the predictive maintenance framework for industrial equipment pose challenges and present opportunities?
3. In what ways does the implementation of predictive maintenance and time series forecasting impact overall cost-effectiveness, equipment lifespan, and operational reliability in diverse industrial sectors?

1.3 Scope of Research

This research will focus on the following aspects of predictive maintenance and time series forecasting:

1. Improving ARIMA-Based Prediction for Industrial Equipment Health Monitoring.
2. Challenges and Opportunities in Integrating Time Series Forecasting for Predictive Maintenance.
3. Impact of Predictive Maintenance and Time Series Forecasting Across Industrial Sectors.

1.4 Objectives of Research

The research objectives are to:

1 Develop and evaluate a comprehensive framework for applying time series forecasting models to predict industrial equipment failures in the food and beverage industry.

2 Identify the most effective time series forecasting model for predicting industrial equipment failures in the food and beverage industry.

3 Develop and implement a prototype predictive maintenance system using the most effective time series forecasting model.

These objectives are more specific and measurable than the previous objectives, and they are more aligned with the research-type nature of the thesis. They also focus on the development and evaluation of a new framework and prototype system, which are significant contributions to the academic literature.

1.5 Benefits of Research

The findings of this thesis with the title "PREDICTIVE MAINTENANCE AND TIME SERIES FORECASTING FOR INDUSTRIAL HEALTH EQUIPMENT" are expected to contribute to the academic literature on predictive maintenance and time series forecasting. Specifically, the research will:

1. Improvements in ARIMA-based prediction methods, leading to more accurate monitoring of industrial equipment health. Result in early detection of potential issues, reducing downtime and enhancing overall operational efficiency.
2. Investigate and evaluate the integration of time series forecasting techniques in predictive maintenance frameworks. Identify challenges, to optimize maintenance schedules, minimize costs, and improve equipment performance.

3. Demonstrate that the implementation of predictive maintenance and time series forecasting positively influences cost-effectiveness by optimizing maintenance schedules and reducing unexpected breakdowns. Additionally, it could contribute to prolonged equipment lifespan and enhanced operational reliability across diverse industrial sectors.

These findings can be used by researchers to further advance the field of predictive maintenance and time series forecasting. Additionally, the findings can be used by practitioners to develop and implement more effective predictive maintenance systems.

BAB II. THEORITICAL BASIS

2.1 Literature Study

No	Author	Title	Method	Conclusion	Year
1	Fernandes (2019)	Fault Detection Mechanism of a Predictive Maintenance System Based on Autoregressive Integrated Moving Average Models	The methodology involves a combination of data preprocessing, time series modeling using ARIMA, anomaly detection, and decision fusion to enhance fault detection in predictive maintenance for CNC machines.	In This paper introduces a fault detection mechanism designed for predictive maintenance systems, specifically addressing anomaly detection in CNC machines. Predictive maintenance systems play a crucial role in anticipating faults in industrial equipment, aiming to mitigate downtime and costly repairs. The challenge arises from the absence of labeled data on past machine faults, rendering traditional supervised learning techniques impractical for accurate predictions. To address this, classical time series	2020

				models, such as autoregressive integrated moving average (ARIMA), are employed to generate prediction intervals based on sensor data monitoring machine conditions. Anomalies are identified by comparing new data to the 95% prediction intervals, with data falling outside these bounds considered anomalous. Recognizing that isolated anomalies may not signify machine issues, the likelihood of a fault is assessed through a 30-minute moving average of anomaly occurrences. Alarms are triggered if the average number of anomalies for a	

				single variable surpasses a user-defined threshold (default = 0.85). Additionally, the mechanism considers simultaneous anomalies across different variables through correlation-based decision fusion. This approach provides an initial solution to the challenge of predictive maintenance in the absence of labeled data. Future research will explore alternative learning methods and mechanisms, facilitating a comparative analysis of results to enhance the effectiveness of fault detection in predictive	

				maintenance systems.	
2	Lin (2019)	Time Series Prediction Algorithm for Intelligent Predictive Maintenance	Time Series Prediction (TSP) algorithm, the Pre-Alarm Module (PreAM), the Death Correlation Index (DCI)	In this , the TSP algorithm is proposed to predict the TD RUL. The illustrative examples reveal that the TSP algorithm can solve the problems that the exponential model may have due to the steep rise and/or steep drop situations. With the TSP model created according to the information criterion that can adapt flexibly, TSP can predict the future trend based on its own historical data. Last but not the least, by choosing the most effective predictors and	2019

				adjusting predictor weights, errors of random processes can be avoided to enhance RUL prediction accuracy. In addition to TSP, the PreAM module and DCI mechanism are proposed in this letter to make alert of immediate maintenance when a TD is likely to shut down shortly and to reveal the possibility of the dead state, respectively. Further, the adaptive exponential model may also be adopted to solve the difficulties of the original exponential model. The development of the adaptive exponential model would be addressed in our future work.	

3	Ayvaz (2021)	Predictive maintenance system for production lines in manufacturing: A machine learning approach using IoT data in real-time.	The use of machine learning algorithms, particularly Random Forest and XG Boost, to develop a predictive maintenance system.	This study introduces a machine learning-based predictive maintenance system designed for manufacturing environments, assessed using real-world IoT data. The model estimates the remaining useful time before machinery failure, demonstrating effectiveness in capturing signals of failure through real-time sensor data. Notably, boosting and bagging ensemble models exhibit strong performance. Future work involves extending the system to diverse production lines. The authorship contribution highlights Serkan Ayvaz and Koray Alpay's	2021

				comprehensive involvement. The authors declare no competing interests. Support is acknowledged from TÜB´ITAK and Procter & Gamble Turkey, with special thanks to Mesut Saban, Ammar Omar, and Orhan Dengiz for their support and feedback.	
4	Carvalho (2019)	A systematic literature review of machine learning methods applied to predictive maintenance	a systematic literature review of Machine Learning (ML) methods applied to Predictive Maintenance (PdM)	This paper presents a systematic literature review focused on Predictive Maintenance (PdM) using Machine Learning (ML) techniques, addressing key research questions outlined in the literature review planning protocol. The analysis revealed that each	2019

				proposed PdM approach tends to cater to specific equipment, making direct comparisons challenging. PdM itself emerges as a vital tool for managing maintenance events, gaining increased feasibility and promise in the wake of Industry 4.0 advancements. Notably, some works in this review employ standard ML methods without parameter tuning, indicating the nascent exploration of PdM by industrial experts. It's emphasized that effective PdM strategy implementation in a plant requires prior adoption of Reliability-centered Maintenance (R2F)	

				and Proactive Maintenance (PvM) strategies for robust data collection, facilitating the design and validation of a PdM strategy. The integration of PdM and ML in applications demonstrates positive outcomes, including cost reduction. The synergy of PdM techniques with advanced sensor technologies is highlighted as a means to prevent unnecessary equipment replacements, leading to cost savings and enhanced safety, availability, and process efficiency. ML techniques such as SVM, RF, ANN, deep learning, and	

				k-means have been successfully applied in designing PdM applications. However, the paper identifies areas for future research, recommending the development of sensing techniques for equipment to improve data quantity and quality, comparative studies of PdM strategies using different ML algorithms, exploration of novel ML algorithms like deep learning, implementation of ensemble learning for more robust predictions, and the creation of new datasets for PdM research. Acknowledging the source of funding and collaboration, this work is	

				conducted under the "Flexible and Autonomous Manufacturing Systems for Custom-Designed Products (FASTEN)" project, supported by the European Union's Horizon 2020 research and innovation program and the Brazilian Ministry of Science, Technology, and Innovation (MCTIC) managed by Rede Nacional de Pesquisa (RNP) under the Grant Agreement 777096.	
5	Pech (2021)	Predictive Maintenance and Intelligent Sensors in Smart Factory: Review	Data-driven predictive maintenance system, machine learning methods,	The advent of the fourth industrial revolution is reshaping the industrial landscape, providing enterprises with unprecedented	2021

			Random Forest, XGBoost.	insights into their production and maintenance activities. To achieve optimal equipment monitoring in this evolving paradigm, the use of multiple sensors of different types and strategically positioned at various locations is imperative. This resourceful approach contributes to precise planning of production capacity and associated equipment maintenance. In the realm of Industrial Equipment Health Monitoring, this strategy aligns with the systematic use of technology to assess and track the condition of industrial machinery. The deployment of highly reliable and	

				low-maintenance devices plays a pivotal role in ensuring accurate multi-sensor equipment monitoring. The study delves into contemporary trends, revealing an increasing focus on sensors, smart factories, and preventive maintenance, driven by Industry 4.0 technologies, such as deep machine learning, the Internet of Things (IoT), and big data analytics. The research addresses key questions related to maintenance processes in smart factories, uncovering four maintenance types in use: predictive maintenance,	

				condition-based maintenance, fault diagnosis for maintenance and prognostics, and remaining useful life analysis. As the number of robots, digitization, and artificial intelligence grows in production lines, the importance of predictive maintenance is on the rise. The study emphasizes three types of sensors mainly used for predictive maintenance: intelligent sensors with connectivity potential, the possibility of IoT integration, and cloud-based data utilization. Challenges identified include big data analytics, interoperability of sensors and	

				maintenance systems, decentralization of maintenance control systems, and the high potential of virtual and nanosensors for the future. The proposed Smart and Intelligent Predictive Maintenance (SIPM) system integrates production, monitoring, planning, and maintenance subsystems through IoT and cloud-based technologies, offering real-time management to reduce economic costs caused by production downtime. From a managerial standpoint, the predictive maintenance system serves as an early	

				warning, aiding in detecting weak signals of strategic impact in high-risk industries. The study acknowledges the responsibility of managers in selecting intelligent sensors based on criteria such as sensitivity, cost, flexibility, and size. Future research avenues include advanced machine learning methods, the "Machine as a Service" (MaaS) model, and evaluating performance models related to reasonable cost. However, the study acknowledges its limitations, including biases in publication collections and the challenge of synonym usage in search strategies.	

				Despite these limitations, the comprehensive analysis provides valuable insights into the evolving landscape of predictive maintenance in smart factories.	

Table 2. 1 Table of Literature Study

2.2 Basic Theory

2.2.1 Predictive Maintenance

Zonta (2020), Dalzochio (2020), Riba (2021)

Predictive maintenance (PdM) has emerged as a prominent focus within multidisciplinary research groups, advocating for the establishment and integration of various research lines spanning data acquisition, infrastructure, storage, distribution, security, and intelligence. (Zonta, 2020) This evolution aligns with the Industry 4.0 revolution, marked by significant global technological advancements. Traditionally, PdM solutions relied on physics-based models, which, while revolutionary at the time, were constrained by costly assumptions, trade-offs, limited generality, and uncertainties. In response to these limitations, the Industry 4.0 era has witnessed a transformative shift towards data-driven PdM methods, leveraging the efficiencies derived from diverse sensors, communication protocols, and computation systems. (Riba 2021) This transition is particularly relevant given the widespread use of different types of sensors, communication protocols, and computation systems, allowing predictive maintenance to evolve towards a hybrid approach that incorporates both data-driven methods and physical modeling. Notably, the integration of low-cost sensors and online sensing technologies into industrial applications contributes to enhancing grid reliability. (Riba, 2021) Despite these advancements, it's noteworthy that hands-on and time-based maintenance methods persist in intensive application. The ultimate objective of predictive maintenance is articulated in its inherent goal: to minimize the impact of failures, reduce downtime, optimize system reliability, and ensure seamless operation. (Zonta, 2020) This goal resonates with the core definition of predictive maintenance, which involves the use of data and technology to predict equipment failures before they occur. The synergy between evolving PdM methods and the broader objectives of the Industry 4.0 revolution emphasizes the role of predictive maintenance in fostering efficiency, reducing costs, and enhancing the overall quality of production process.

2.2.2 Time Series Forecasting

(Torres, José F, 2021), (Lim, Bryan, Stefan Zohren, 2021)

The complexity of time series datasets is notably heightened by the presence of time-dependent confounding effects, introducing challenges in the analysis and interpretation of temporal patterns. Often, time series data exhibits a hierarchical structure, featuring logical groupings among trajectories, particularly evident in applications like time series prediction. This inherent structure has led researchers to explore advanced modeling approaches, specifically in the form of continuous-time and hierarchical models, to effectively capture and navigate the intricate dependencies within the data. (Lim, Bryan, Stefan Zohren, 2021)

As the significance of time series forecasting continues to grow, the field has become an increasingly intensive area of research, with a surge in interest and exploration, especially in recent years. The time series forecasting problem, a fundamental aspect of this research, is initially formulated by considering its mathematical foundations. This formulation is essential for establishing a rigorous framework to address the challenges posed by time-dependent confounding effects and the hierarchical structure inherent in time series datasets. (Torres, José F, 2021)

In the context of time series forecasting, the definition expands beyond predicting future values to encompass the recognition and understanding of temporal patterns. The benefits of employing continuous-time and hierarchical models lie in their ability to navigate the complexities introduced by time-dependent confounding effects and hierarchical structures, enhancing the accuracy of predictions. (Lim, Bryan, Stefan Zohren, 2021) The suitability of these forecasting methods is evident in their capacity to address the evolving challenges within time series datasets, ultimately contributing to more informed decision-making processes and improved forecasting accuracy in various applications. (Torres, José F, 2021)

2.2.3 Industrial Equipment Health Monitoring

Akpudo (2022)

The importance of employing a comprehensive approach to equipment monitoring by utilizing multiple sensors of different types strategically placed at various locations. This strategy aligns seamlessly with the principles of Industrial Equipment Health Monitoring, which involves systematically leveraging technology to assess and track the condition of industrial machinery. The call for employing multiple sensors in different locations reflects the recognition of the diverse factors influencing equipment health. This resourceful paradigm enhances the precision of multi-sensor equipment monitoring, providing a nuanced understanding of the machinery's performance. The suitability of this approach lies in its ability to detect anomalies and potential issues, facilitating proactive maintenance measures. Industrial Equipment Health Monitoring, as embodied by the use of multiple sensors, offers a proactive and comprehensive method for maintaining optimal machinery performance. By continuously collecting and analyzing data from these sensors, it enables real-time insights into equipment health, fostering timely decision-making and contributing to the overall reliability and efficiency of industrial systems. (Akpudo, 2022)

2.2.4 ARIMA

The ARIMA method is an approach that generates forecasts based on historical data patterns. It is a combination of the AR (Autoregressive) model, which explains the movement of a variable through the variable itself in the past, and the MA (Moving Average) model, which examines the movement of residuals in the past. (Rezaldi & Sugiman, 2021, p. 612)

2.2.5 Angular

AngularJS is a comprehensive JavaScript web application framework with a complete frontend MVC framework. It is based on Google and provides a rapid way to build single-page web applications. (Hsb et al., 2021, p. 87)

2.2.6 ExpressJS

Express.js adalah framework yang bekerja pada aplikasi Node.js yang minimalis dan fleksibel. Express.js juga memiliki dokumentasi yang lengkap dan penggunaannya yang cukup mudah, dapat membuat kita mengembangkan berbagai produk seperti aplikasi web ataupun RESTful API. (Widyoutomo et al., 2021, 4)

2.2.7 NodeJS

Node.js is a server-side platform built on Google Chrome's V8 JavaScript engine, developed by Ryan Dahl in 2009. It is an open-source application that is entirely free and widely utilized by thousands of developers worldwide for building server-side and network applications. Node.js serves as a runtime environment for JavaScript. The runtime environment of Node.js includes everything web developers need to execute programs written in JavaScript (Node.js). (Widyoutomo et al., 2021, p. 4)

2.2.8 Tailwind

Tailwind is a CSS framework used to fulfill basic needs in building website user interface components, such as setting margins, object sizes, positions, colors, and more. Tailwind facilitates the creation of components without being bound to the design styles of other frameworks. (Arhandi et al., 2020)

2.2.9 MYSQL

MySQL is an open-source SQL database management system that is currently the most popular. The MySQL database system supports features such as multithreading, multi-user, and SQL Database Management System (DBMS). This database is designed for the needs of a fast, reliable, and user-friendly database system. MySQL is a multiuser database that uses the Structured Query Language (SQL). (Sudaria et al., 2021, p. 104)

2.2.10 Javascript

JavaScript is: (1) a high-level programming language; (2) client-side; (3) object-oriented, and (4) loosely typed. (Mariko, 2019, p. 84)

2.2.11 Typescript

TypeScript is a modern-era development language for JavaScript. It is a statically compiled language designed for writing clear and straightforward JavaScript code. It can run on NodeJS or browsers that support ECMAScript or newer versions. TypeScript provides optional static typing, classes, and interfaces. (Arhandi et al., 2019)

BAB III. RESEARCH METHODOLOGY

3.1. Time and Place of Research

3.1.1 Research Time

The time used for this research was carried out over a period of 6 months, with 1 month dedicated to data collection and 1 month for processing the data, which includes presenting it in the form of a thesis and the guidance process that took place.

3.1.2 Research Location

The research was conducted at the company PT.XYZ, which operates in the food and beverage industry.

3.2. Data Collection Methods

3.2.1 Observation

Observation is conducted to gather the necessary data for constructing this predictive maintenance integration system. In-depth observation is necessary because it is likely that the data in the database is not in one easily accessible location. Conducting data exploration with the assistance of one of the clients is essential to ensure that the calculations and programming logic during system development stay on track. We are collecting vibration data, specifically at 2-hour intervals and also under thermal conditions with consistent frequency. At the same time, we're focusing on temperature measurements, capturing data both at 2-hour intervals and 3-hour intervals, while also considering a thermal window of 3 hours. Additionally, our observational approach extends to ampere readings, where we methodically gather data for the R, S, T phases, while also factoring in the relevant frequency.

3.2.2 Interview

Interviews are conducted to ensure that the development of the energy management system is more directed and aligned with the needs. Additionally, interviews will also assist in understanding the system to be worked on.

3.2.3 Literature Review

A literature review is conducted to study literature related to the research. The references used by the author are obtained from scientific journals.

3.3 Data Processing Methods

After the data has been successfully collected, the next step is to process the data using predefined calculations. Once the data processing is complete, the next step is to analyze whether the processed data meets the requirements of PT.XYZ. Additionally, an analysis is conducted to determine whether the processed data is suitable for inclusion in the ARIMA method or if the data is in the form of a time series

3.3.1 ACF & PACF

The ARIMA model can be determined through the calculation of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). The method used to obtain a time series model is by utilizing the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) (Yakubu & Saputra, 2022, p. 81). The results of these calculations can assist in determining the suitable model for use in the ARIMA method for forecasting.

The Autocorrelation Function (ACF) is calculated using the following formula:

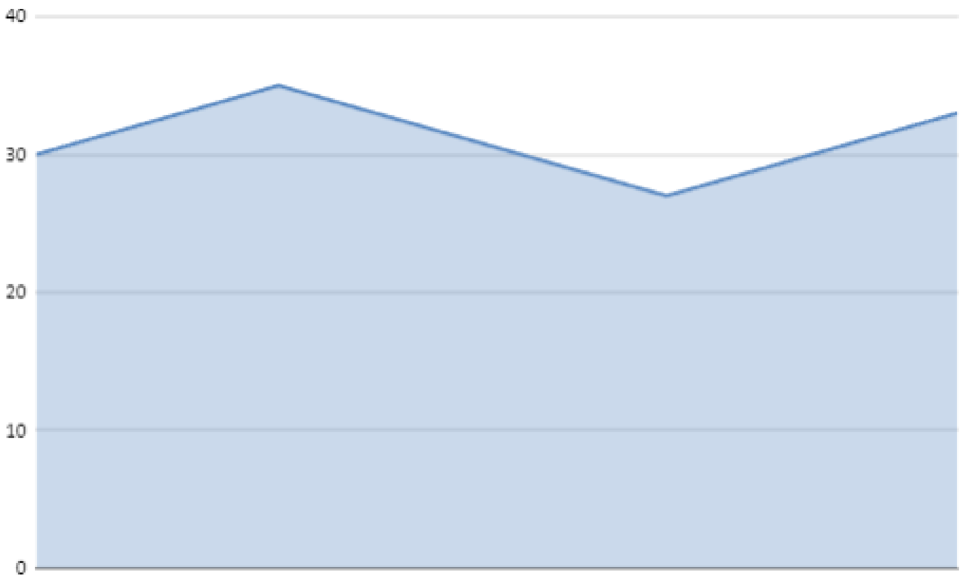
$$ACF(t) = \frac{Cov(y_t, y_{t-k})}{Variance(y_t)}$$

The ACF calculates the correlation between observations at time t and observations at time t - k. The values of ACF range between -1 and 1, where a value of 1 indicates perfect correlation between observations at time t and t - k , a value of 0 indicates no correlation between the two observations, and a value of -1 indicates perfect but opposite correlation between the two observations. Sample autocorrelation should be calculated up to lag k, where k is approximately equal to T/4

As an example, there is data as follows:

10	11	12	13	14	15	14	13	12	11	10	9	8	7	8	9	10	11	12	13

If transformed into a diagram, it will create a pattern approximately as follows:



To calculate ACF, the first step is to calculate Cov(yt, yt-k) beforehand. Calculating the coefficients for lag 0, lag 1, and so on (lag k) can be done as follows:

`=(B2-AVERAGE($B$2:$B$21))*(B2-AVERAGE($B$2:$B$21))`

B	C	D	E
data	lag 0	lag 1	lag 2
10	1,21		

`=(B3-AVERAGE($B$2:$B$21))*(B2-AVERAGE($B$2:$B$21))`

B	C	D	E
data	lag 0	lag 1	lag 2
10	1,21		
11	0,01	0,11	

```
=(B4-AVERAGE($B$2:$B$21))*(B2-AVERAGE($B$2:$B$21))
```

B	C	D	E
data	lag 0	lag 1	lag 2
10	1,21		
11	0,01	0,11	
12	0,81	-0,09	-0,99

In the above image, the first step to obtain the coefficients is to calculate ((y(t)-MEAN(y))*(y(t-k)-MEAN(y))). Continue the calculation until all data is included, as shown in the following figure :

data	lag 0	lag 1	lag 2	lag 3	lag 4	lag 5
10	1,21					
11	0,01	0,11				
12	0,81	-0,09	-0,99			
13	3,61	1,71	-0,19	-2,09		
14	8,41	5,51	2,61	-0,29	-3,19	
15	15,21	11,31	7,41	3,51	-0,39	-4,29
14	8,41	11,31	8,41	5,51	2,61	-0,29
13	3,61	5,51	7,41	5,51	3,61	1,71
12	0,81	1,71	2,61	3,51	2,61	1,71
11	0,01	-0,09	-0,19	-0,29	-0,39	-0,29
10	1,21	0,11	-0,99	-2,09	-3,19	-4,29
9	4,41	2,31	0,21	-1,89	-3,99	-6,09
8	9,61	6,51	3,41	0,31	-2,79	-5,89
7	16,81	12,71	8,61	4,51	0,41	-3,69
8	9,61	12,71	9,61	6,51	3,41	0,31
9	4,41	6,51	8,61	6,51	4,41	2,31
10	1,21	2,31	3,41	4,51	3,41	2,31
11	0,01	0,11	0,21	0,31	0,41	0,31
12	0,81	-0,09	-0,99	-1,89	-2,79	-3,69
13	3,61	1,71	-0,19	-2,09	-3,99	-5,89

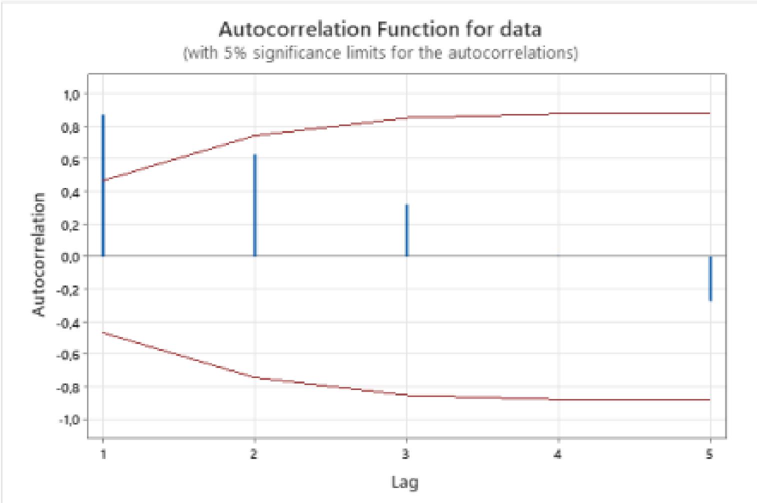
The next step is to sum the results for each lag and divide it by the variance(yt). Based on the formula that has been explained, the variance(yt) is equal to the sum of results from lag 0. Calculate the entire dataset, and it will result in something approximately like the following figure :

period	data	lag 0	lag 1	lag 2	lag 3	lag 4	lag 5
1	10	1,21					
2	11	0,01	0,11				
3	12	0,81	-0,09	-0,99			
4	13	3,61	1,71	-0,19	-2,09		
5	14	8,41	5,51	2,61	-0,29	-3,19	
6	15	15,21	11,31	7,41	3,51	-0,39	-4,29
7	14	8,41	11,31	8,41	5,51	2,61	-0,29
8	13	3,61	5,51	7,41	5,51	3,61	1,71
9	12	0,81	1,71	2,61	3,51	2,61	1,71
10	11	0,01	-0,09	-0,19	-0,29	-0,39	-0,29
11	10	1,21	0,11	-0,99	-2,09	-3,19	-4,29
12	9	4,41	2,31	0,21	-1,89	-3,99	-6,09
13	8	9,61	6,51	3,41	0,31	-2,79	-5,89
14	7	16,81	12,71	8,61	4,51	0,41	-3,69
15	8	9,61	12,71	9,61	6,51	3,41	0,31
16	9	4,41	6,51	8,61	6,51	4,41	2,31
17	10	1,21	2,31	3,41	4,51	3,41	2,31
18	11	0,01	0,11	0,21	0,31	0,41	0,31
19	12	0,81	-0,09	-0,99	-1,89	-2,79	-3,69
20	13	3,61	1,71	-0,19	-2,09	-3,99	-5,89
Total	222	93,8	81,89	58,98	30,07	0,16	-25,75
ACF	93,8	1	0,8730277186	0,6287846482	0,320575693	0,00170575693	-0,2745202559

The calculation results in Figure 3.6 can be transformed into a diagram like Figure 3.7. To prove the accuracy of the calculations, I used statistical software, inputting all available data.

Autocorrelations

Lag	ACF	T	LBQ
1	0,873028	3,90	17,65
2	0,628785	1,77	27,32
3	0,320576	0,79	29,97
4	0,001706	0,00	29,98
5	-0,274520	-0,65	32,19



The calculation results from the statistical software are consistent with the manual calculations. The ACF calculation has been completed. As for PACF, it can be calculated using the ACF data that has already been computed. The formula for PACF is as follows:

- Lag 1 in PACF is same from Lag 1 in ACF
- Lag 2 in PACF can be formulated as :

$$PACF(2) = \frac{Cov(y_t, y_{t-2} | y_{t-1})}{\sqrt{Var(y_t | y_{t-1}) Var(y_{t-2} | y_{t-1})}}$$

- Lag 3 in PACF can be formulated as :

$$PACF(2) = \frac{Cov(y_t, y_{t-2} | y_{t-1})}{\sqrt{Var(y_t | y_{t-1}, y_{t-2}) Var(y_{t-3} | y_{t-1}, y_{t-2})}}$$

Similarly, the process continues up to lag k. Typically, matrix manipulations related to the covariance matrix of multivariate distributions are used to determine PACF estimates. Similar to ACF, the values of PACF range between -1 and 1, where a value of 1 indicates perfect correlation between observations at time t and t-t, a value of 0 indicates no correlation between the two observations, and a value of -1 indicates perfect but opposite correlation between the two observations.

As previously explained, calculating PACF usually involves matrix manipulations, and the matrix can be modeled approximately as follows:

$$\begin{pmatrix} \rho(0) & \rho(1) & \cdots & \rho(k-1) \\ \rho(1) & \rho(0) & \cdots & \rho(k-2) \\ \vdots & \vdots & \vdots & \vdots \\ \rho(k-1) & \rho(k-2) & \cdots & \rho(0) \end{pmatrix} \begin{pmatrix} \phi_{k1} \\ \phi_{k2} \\ \vdots \\ \phi_{kk} \end{pmatrix} = \begin{pmatrix} \rho(1) \\ \rho(2) \\ \vdots \\ \rho(k) \end{pmatrix}$$

Based on the matrix in Figure 3.9 and the data in Table 3.1, along with the matrix calculation results in Figure 3.6, the left matrix in Figure 3.9 can be arranged as follows:

1	0,8730277186	0,6287846482	0,320575693	0,00170575693	-0,2745202559	-0,4547974414
0,8730277186	1	0,8730277186	0,6287846482	0,320575693	0,00170575693	-0,2745202559
0,6287846482	0,8730277186	1	0,8730277186	0,6287846482	0,320575693	0,00170575693
0,320575693	0,6287846482	0,8730277186	1	0,8730277186	0,6287846482	0,320575693
0,00170575693	0,320575693	0,6287846482	0,8730277186	1	0,8730277186	0,6287846482
-0,2745202559	0,00170575693	0,320575693	0,6287846482	0,8730277186	1	0,8730277186
-0,4547974414	-0,2745202559	0,00170575693	0,320575693	0,6287846482	0,8730277186	1

Meanwhile, the second matrix can be filled with the ACF calculation results from lag 1 to lag k, adjusting to the size of the first matrix. The first matrix can be adjusted according to needs, but similar to ACF, sample PACF should be calculated up to lag K, where K is approximately equal to T/4.

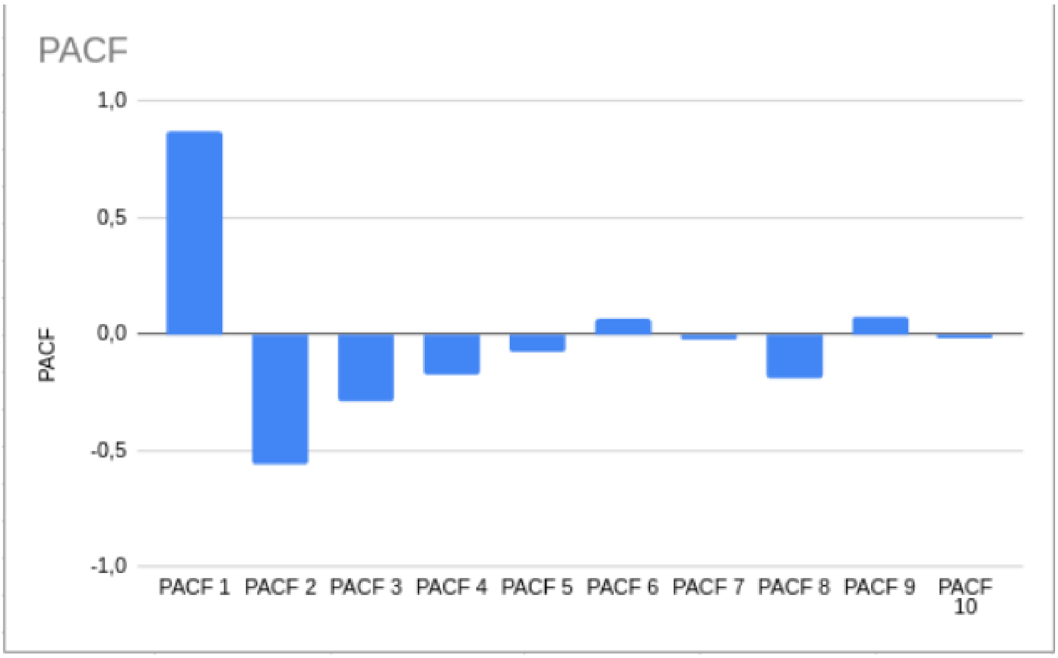
As explained in the formula, the PACF for lag 1 will be the same as the ACF for lag 1. Meanwhile, the PACF for lag 2 can be calculated as follows:

```
=MMULT(MMULT(MINVERSE(MMULT(E25:F26;E25:F26));E25:F26);D26:D27)
```

C	D	E	F	
	1	PACF 1	PACF 2	PACF 3
0,8730277186	0,8730277186	0,8730277186	1,362701813	1,202
-0,5608918063	0,6287846482		-0,5608918063	-0,1713

As observed, matrix multiplication will result in a new matrix of the same size as the multiplier matrix. For E25:F26, it is a 2x2 matrix from the top left of Figure 3.10, while D26:D27 is a 1x2 matrix containing lag 1 up to lag 2. For the PACF results, take the bottommost values from the matrix calculation. Continue the PACF calculation up to lag k.

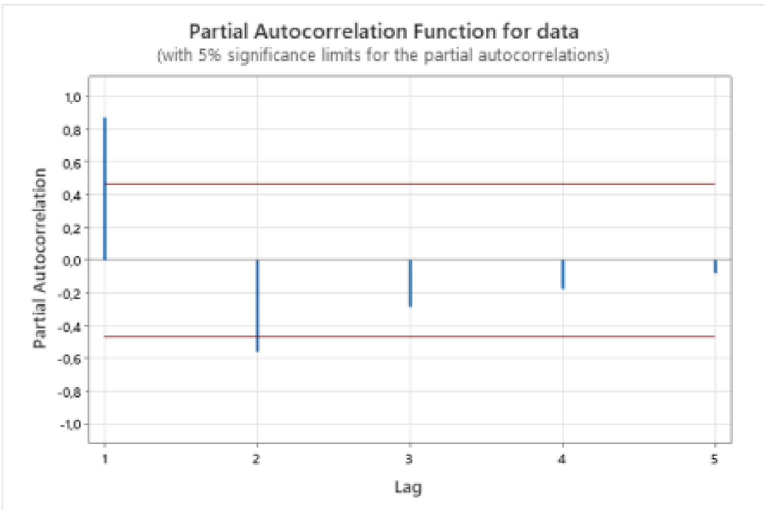
		1	PACF 1	PACF 2	PACF 3	PACF 4	PACF 5	PACF 6
PACF 1	0,8730277186	0,8730277186	0,8730277186	1,362701813	1,202365438	1,151876183	1,137938349	1,143085671
PACF 2	-0,5608918063	0,6287846482		-0,5608918063	-0,1713502473	-0,2016145539	-0,2074142707	-0,201822671
PACF 3	-0,2858597203	0,320575693			-0,2858597203	-0,07349494828	-0,08940498487	-0,08357330418
PACF 4	-0,1766224854	0,00170575693				-0,1766224854	-0,08572432418	-0,07219517029
PACF 5	-0,0789131354	-0,2745202559					-0,0789131354	-0,153138226
PACF 6	0,06522769067	-0,4547974414						0,06522769067



The PACF calculation results in Figure 3.12 can be transformed into a diagram as shown in Figure 3.13. To verify the accuracy of these calculations, I used statistical software, inputting all available data.

Partial Autocorrelations

Lag	PACF	T
1	0,873028	3,90
2	-0,560892	-2,51
3	-0,285860	-1,28
4	-0,176622	-0,79
5	-0,078913	-0,35



From the results of the statistical software calculation, it can be observed that the output matches the manually calculated results.

3.3.2 Determination of AR (Auto Regressive)

In the ARIMA model, the determination of AR can be selected through the calculations of previously obtained ACF and PACF. The criteria that must be fulfilled by ACF and PACF to be decisive for AR in the ARIMA model are as follows:

Process	ACF	PACF
AR(*p*)	Decreasing exponentially or exhibiting a sinusoidal wave pattern	Cut off at lag *p*.

Based on the PACF in Figure 3.14, it shows that the last significant lag is at lag 2, indicating a potential suitable AR model for ARIMA is AR(2). From this determination, a preliminary ARIMA model of ARIMA(2,0,0) is obtained.

3.3.3 Determination of MA (Moving Average)

Not much different from the determination of AR in the ARIMA method, the determination of MA can also be selected through the calculations of previously obtained ACF and PACF. The criteria that must be fulfilled by ACF and PACF to be decisive for MA in the ARIMA model are as follows:

Process	ACF	PACF
AR(*p*)	Decreasing exponentially or exhibiting a sinusoidal wave pattern	Cut off at lag *p*.
MA(*q*)	Cut off at lag *p*.	Decreasing exponentially or exhibiting a sinusoidal wave pattern

Based on the ACF in Figure 3.8, it shows that the last significant lag is at lag 1, indicating a potential suitable MA model for ARIMA is MA(1). From the determination of AR and MA, an ARIMA model of ARIMA(2,0,1) is obtained.

3.3.4 ARIMA

Determining an ARIMA model involves several stages, including ACF and PACF calculations, AR model determination, and MA model determination. In ACF and PACF calculations, it is possible to obtain results in the form of White Noise. White noise is a condition where all conditions, as shown in Figures 3.15 and

3.16, are not met. If the ACF and PACF calculations result in White Noise, the next step is to perform differencing.

In essence, the ARIMA model has three components denoted as ARIMA(p, d, q), where p refers to autoregressive (AR) order, q refers to moving average (MA) order, and d is the differencing level. In the previous steps, it has been determined that the suitable ARIMA model is ARIMA(2,0,1), where it utilizes AR(2) and MA(1) without differencing.

ARIMA(2,0,1) can be formulated as follows:

$$y(t) = c + AR(1) \times y_{t-1} + AR(2) \times y_{t-2} + MA(1) \times e_{t-1} + e_t$$

where :

- y(t) is time series data at t time
- c is constant
- AR(1) and AR(2) is coefficient from AR(1) and AR(2)
- MA(1) is coefficient from MA(1)
- e(t) is residual at t time

To assist in determining the required constants and coefficients, I am using statistical software. For the ARIMA(2,0,1) model itself, it will approximately yield the following data :

Final Estimates of Parameters

Type	Coef	SE Coef	T-Value	P-Value
AR 1	1,8440	0,0470	39,20	0,000
AR 2	-0,9908	0,0451	-21,97	0,000
MA 1	0,865	0,310	2,79	0,013
Constant	1,6183	0,0130	124,44	0,000
Mean	11,0264	0,0886		

From Figure 3.17, it is known that the generated constant is 1.6183, while the coefficients for MA(1), AR(1), and AR(2) are 0.865, 1.8440, and -0.9908, respectively. Despite these results, there is still missing data, namely the residual or error e_t. The method to find e_t can be carried out as follows:

=AVERAGE(B2:B3)	=ABS(B3-F3)/B3
F	G
1 period MA	error
10,5	4,55%
11,5	4,17%
12,5	3,85%
13,5	3,57%
14,5	3,33%
14,5	3,57%
13,5	3,85%
12,5	4,17%
11,5	4,55%
10,5	5,00%
9,5	5,56%
8,5	6,25%
7,5	7,14%
7,5	6,25%
8,5	5,56%
9,5	5,00%
10,5	4,55%
11,5	4,17%
12,5	3,85%

To determine e_t, one can use Simple Moving Average (SMA), where SMA can help determine the error at time t. Determining the error at time t can be done by subtracting the actual value from the prediction and dividing it by the actual value. For SMA(1), it can be calculated by finding the average from t to $t - 1$, which becomes a temporary prediction.

After obtaining all the necessary data, the next step is to input all available data to generate forecasts. The results will be approximately as follows:

fx =1,61583+(1,844*C4)+(-0,9908*D4)+(0,865*G3)+G4

A	B	C	D	E	F	G
period	data	lag 1	lag 2	forecast	1 period MA	error
1	10					
2	11	10			10,5	4,55%
3	12	11	10	12,07	11,5	4,17%
4	13	12	11	12,92	12,5	3,85%
5	14	13	12	13,77	13,5	3,57%
6	15	14	13	14,62	14,5	3,33%
7	14	15	14	15,47	14,5	3,57%
8	13	14	15	12,64	13,5	3,85%
9	12	13	14	11,79	12,5	4,17%
10	11	12	13	10,94	11,5	4,55%
11	10	11	12	10,10	10,5	5,00%
12	9	10	11	9,26	9,5	5,56%
13	8	9	10	8,41	8,5	6,25%
14	7	8	9	7,58	7,5	7,14%
15	8	7	8	6,72	7,5	6,25%
16	9	8	7	9,54	8,5	5,56%
17	10	9	8	10,38	9,5	5,00%
18	11	10	9	11,23	10,5	4,55%
19	12	11	10	12,07	11,5	4,17%
20	13	12	11	12,92	12,5	3,85%
		13	12	13,73		

From Figure 3.20, you can see the forecast results. The obtained results are close to the actual values. After the actual values, forecasts can use the previous forecast values to obtain the next forecast. The previous actual values strongly influence the upcoming forecast values. The verification of how close the forecast results are to the actual values can be calculated using MAPE (Mean Absolute Percentage Error).

3.4 System Design

3.4.1 Use Case

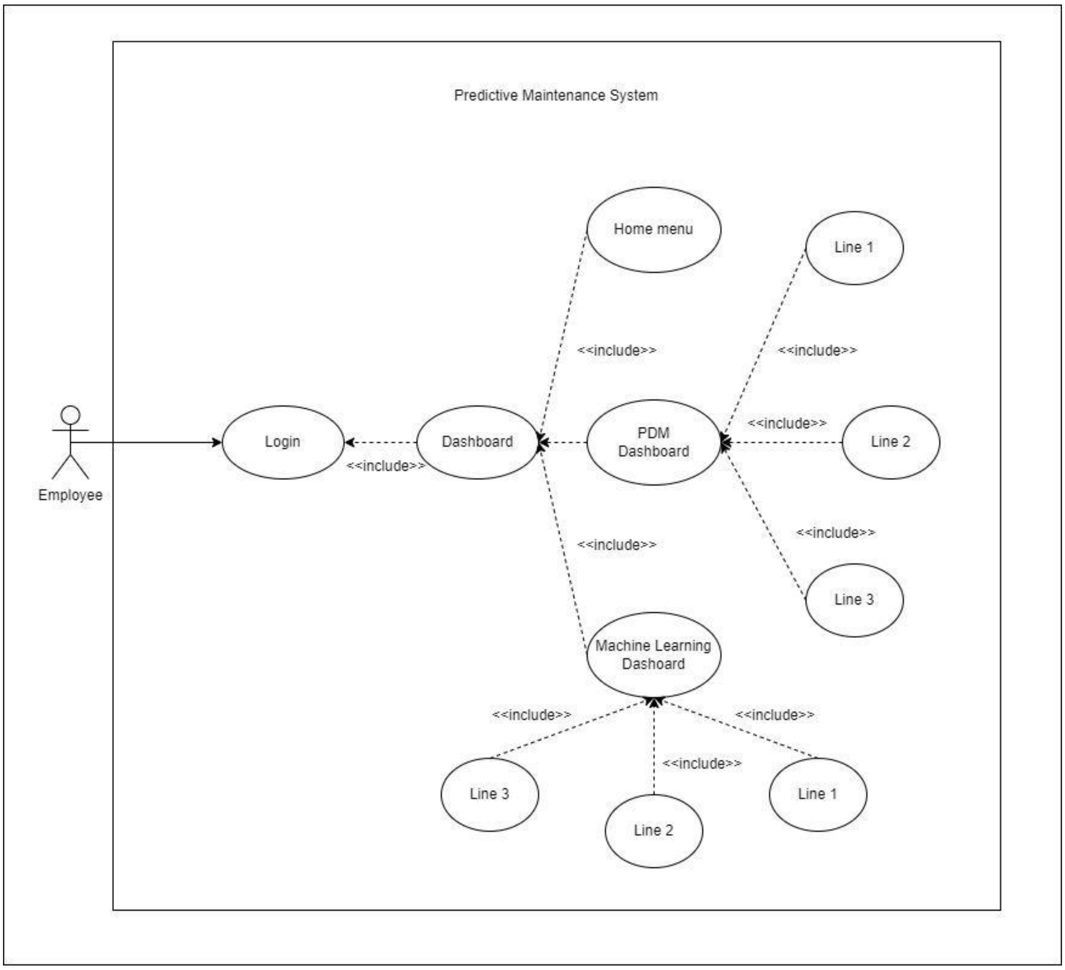


Figure 3. 1 Use Case DIagram

In the above use case diagram, there is one user, namely the employee. Employees can access all available features with the condition that they log in first. The employee plays an exclusive role in the login feature. There are several features within other features, as seen in the use case diagram above.

3.4.2 Flow Chart

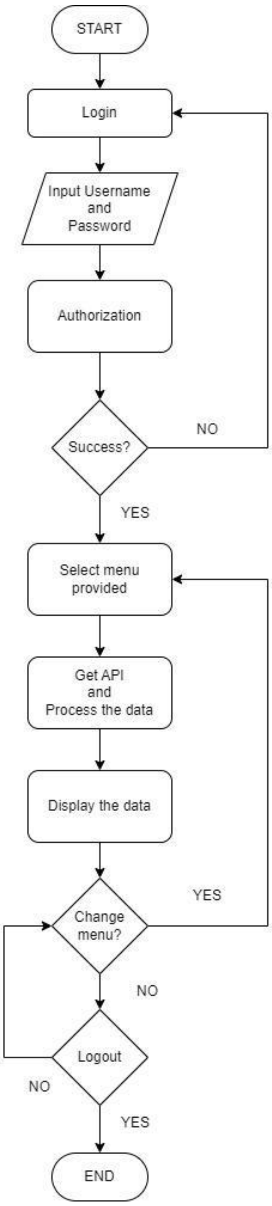


Figure 3. 2 Flow Chart Diagram

The flowchart above represents the flow of the system to be developed. Initially, when guests access the system, they will be directed to log in first. After logging in, employees will be directed to the dashboard and available menus. Whenever a menu is selected, there is a data processing process, and the resulting data is then displayed.

3.4.3 Activity Diagram

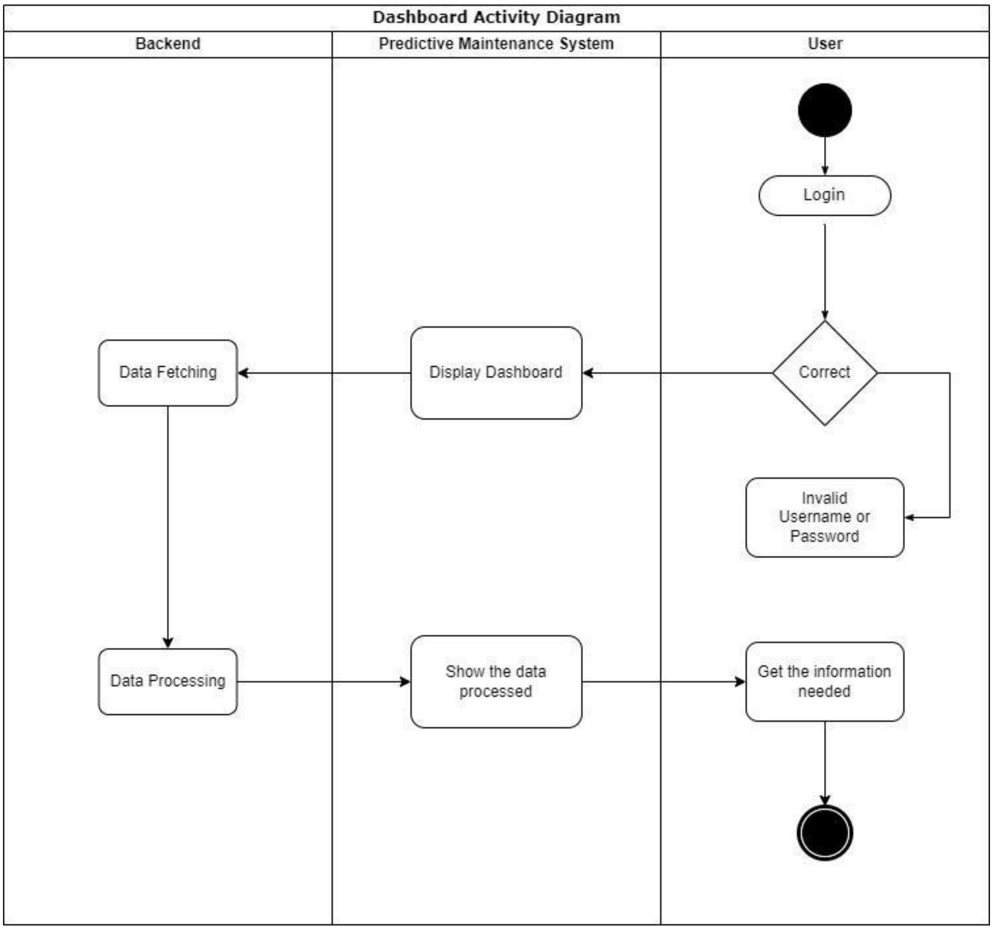


Figure 3. 3 Activity Diagram Dashboard

The activity diagram for the dashboard illustrates the interaction between users and the system's data. The user initiates the process by logging in. Once logged in successfully, the system directs the user to the dashboard, where they can access information that has been processed by the system.

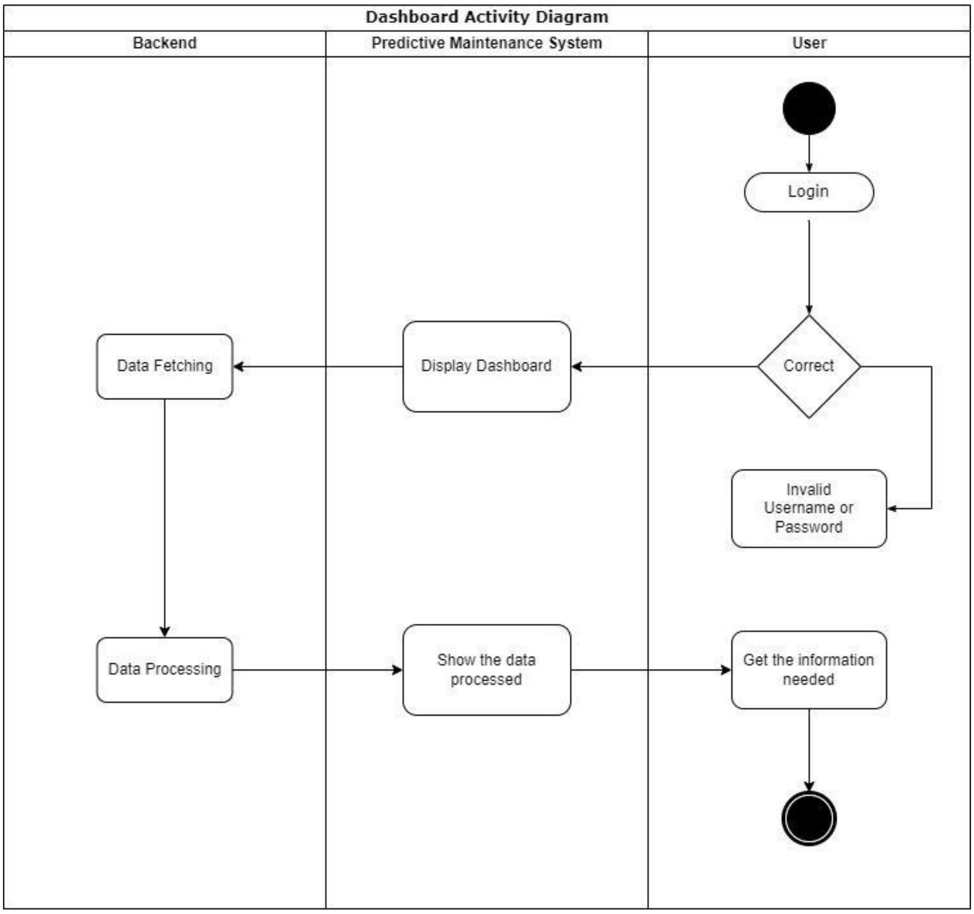


Figure 3. 4 Activity Diagram Dashboard Detail

In the activity diagram for the detailed dashboard, the relationship between the user and the available data is depicted. The user's activities closely resemble those in the dashboard activity diagram. Initially, the user logs in, and upon successful login, they are directed to the detailed dashboard. On the detailed dashboard, users can access information processed by the system.

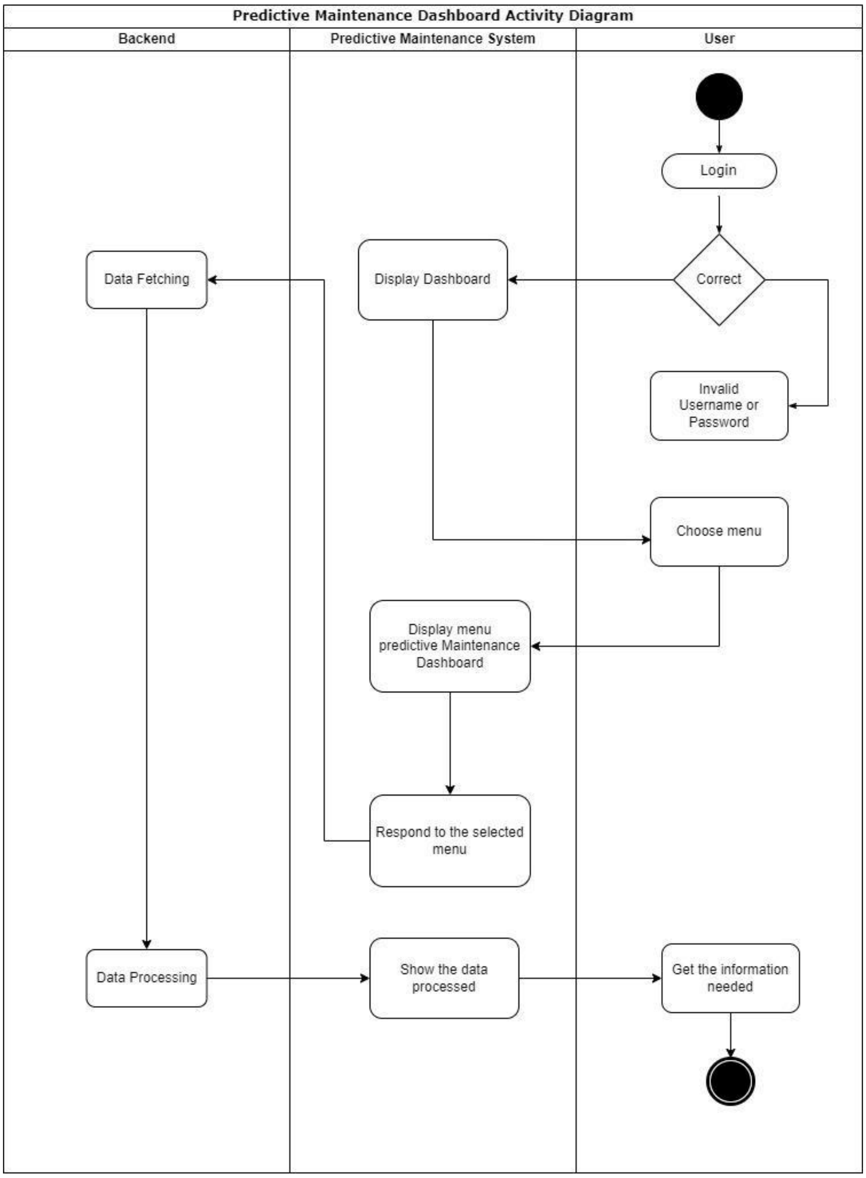


Figure 3. 5 Activity Diagram Predictive Maintenance

In the activity diagram for predictive maintenance, the relationship between the user and the available data is illustrated. The user's activities start with logging in, and upon successful login, the user selects a menu. If the user chooses the predictive maintenance menu, they will be directed to the predictive maintenance page. The system responds accordingly, providing the user with information that has been generated.

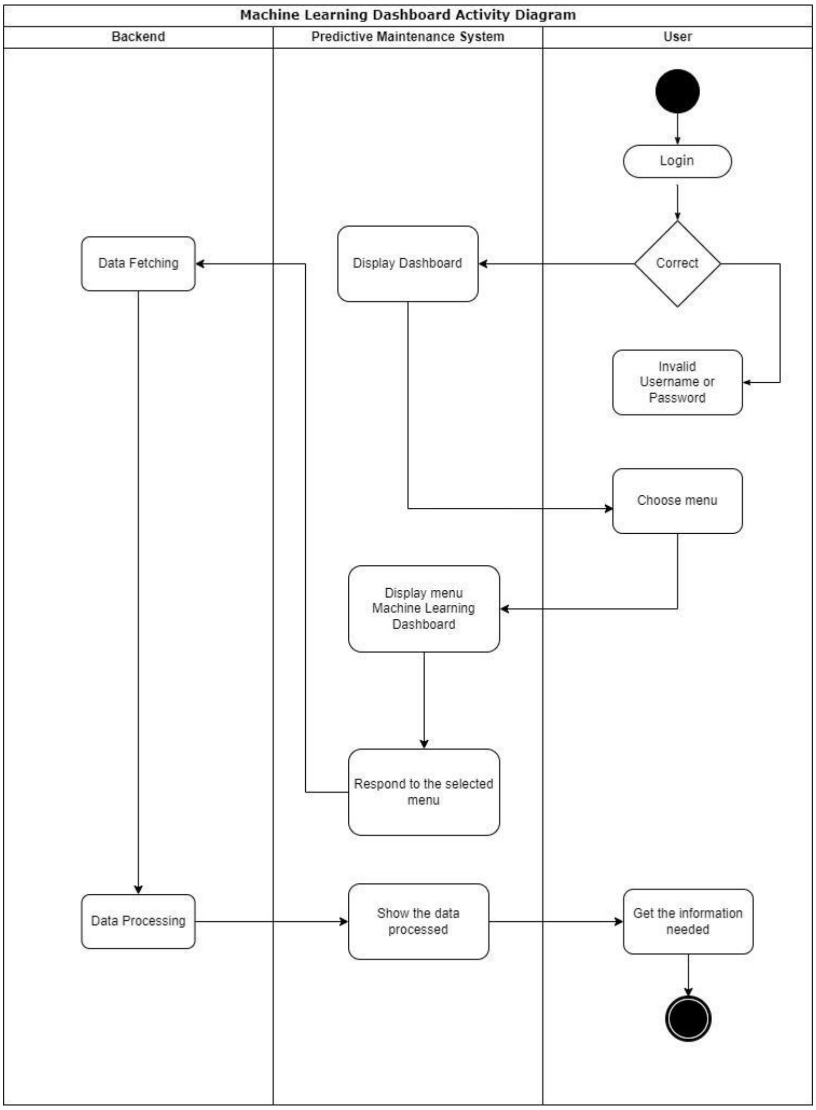


Figure 3. 6 Activity Diagram Machine Learning

In the activity diagram for machine learning, the relationship between the user and the available data is depicted. The user's activities begin with logging in, and upon successful login, the user selects a menu. If the user chooses the machine learning menu, they will be directed to the machine learning page. The system responds accordingly, providing the user with information that has been generated through machine learning processes.

3.5 System Testing

The trial of the system in this maintenance management system will use the MAPE(Mean Absolute Percentage Error) method to test whether the results from ARIMA are close or not. Mean Absolute Percentage Error (MAPE) is a measure of relative error. MAPE expresses the percentage error of prediction or forecast results compared to actual results during a specific period, providing information about the percentage of errors that are too high or too low.

The formula for calculating MAPE is as follows:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Ai-Fi}{Ai}\right| \times 100\%$$

Where:

- n is sample size
- Ai is actual value
- Fi is predictive value

Based on the calculations performed in sub-section 3.3, the example calculation of MAPE will be as follows:

=ABS(B4-E4)/B4

M
0,00606790404
0,006189753452
0,01662760597
0,02562292063
0,1049412585
0,02775504649
0,01736950855
0,005006707989
0,009954818182
0,02842617284
0,05179819444
0,0823030102
0,1597855357
0,06020533951
0,03834855556
0,02066677686
0,00606790404
0,006189753452

The first step is to calculate the absolute value of (actual value(t) - forecast(t))/actual value(t). In Excel, you can use =ABS. Once all values are calculated, the next step is to complete the formula as previously explained.

fx =(1/20)*SUM(M1:M18)

L	M
	0,00606790404
	0,006189753452
	0,01662760597
	0,02562292063
	0,1049412585
	0,02775504649
	0,01736950855
	0,005006707989
	0,009954818182
	0,02842617284
	0,05179819444
	0,0823030102
	0,1597855357
	0,06020533951
	0,03834855556
	0,02066677686
	0,00606790404
	0,006189753452
MAPE	3,37%

From the obtained results, it can be determined that the MAPE obtained from the ARIMA(2,0,1) model and the data in Table 3.1 is 3.37%. The smaller the percentage obtained from MAPE calculations, the higher the accuracy level. The general criteria for MAPE values are:

- MAPE < 10% = Very good accuracy level.
- 10% <= MAPE < 20% = Good accuracy level.
- 20% <= MAPE < 50% = Acceptable accuracy level.
- MAPE >= 50% = Poor accuracy level.

Reason for Selecting MAPE :

The decision to adopt MAPE for this evaluation is underpinned by several distinct advantages it offers over alternative error metrics:

1. Relative Measure: MAPE's inherent ability to provide a relative percentage-based error evaluation facilitates a more intuitive

understanding of forecast accuracy in relation to actual values. This relative measure contrasts with metrics such as Mean Absolute Error (MAE) or Root Mean Square Error (RMSE), which lack the percentage-based perspective.

2. Interpretability: The percentage-based representation of MAPE enhances its interpretability, ensuring that stakeholders, regardless of their familiarity with forecasting methodologies, can comprehend the accuracy of predictions effectively.
3. Scale Independence: MAPE's scale-independent nature eliminates the need for normalization when comparing forecast accuracy across diverse datasets or time series, thereby simplifying the evaluation process.
4. Weighting Large Errors: By proportionally emphasizing large errors, MAPE ensures that significant forecasting inaccuracies receive appropriate attention, thereby enhancing the robustness and reliability of the evaluation.
5. Simplicity: The computational simplicity associated with calculating MAPE, which relies solely on absolute error and actual values, underscores its practicality and efficiency in assessing forecast accuracy.

In summary, while acknowledging the merits of other error metrics such as MAE, RMSE, and MASE, the selection of MAPE for evaluating the ARIMA forecasting results in this maintenance management system reflects a deliberate choice. This decision is grounded in MAPE's alignment with the system's objectives, its relative ease of interpretation, and its robustness in capturing forecast accuracy effectively.

BAB IV. RESEARCH SCHEDULE

Tabel 4.1 Research Schedule Table

No	Activity	November				December				January				February				March				April				May			
		1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
1	Title Proposal																												
	Concept Idea Exploration																												
	Thesis Topic Proposal																												
	Supervisor Proposal																												
2	PraProposal																												
	Thesis Making Guidance																												
	Thesis Defence																												
3	Literature Study																												
	Searching and Studying Literature																												
	Searching and Studying System Concepts																												
	Studying Methods Used																												
4	Analysis																												
	Data Collection																												
	Data Analysis																												
	Functional Requirement Analysis																												
	Non Functional Requirement Analysis																												
5	System Design																												
	Flowchart Design																												
	DFD Design																												
	ERD Design																												
	Mockup System Design																												
6	System Implementation																												
	Developing Backend																												
	Developing Frontend																												
	Developing REST API																												
7	System Testing																												
	Functional System Testing																												
	System Perform Testing																												
8	Analysis of Report Results and Conclusions																												
	Making Report																												

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