RELIABILITY OPTIMIZATION FOR BATIK PRINTING MACHINE MAINTENANCE USING DATA ANALYTICS BY CONSIDERING A HYBRID OF LSTM AND GRU METHODS

UNDERGRADUATE THESIS

Submitted to the International Undergraduate Program in Industrial Engineering in Partial Fulfilment of Requirement for the Degree of Sarjana Teknik at the Faculty of Industrial Technology

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Demikian surat keterangan penelitian ini kami buat. Atas perhatiannya dan kerja samanya kami mengucapkan terima kasih.

Wassalamu'alaikum Warohmatullahi Wabarokaatuh

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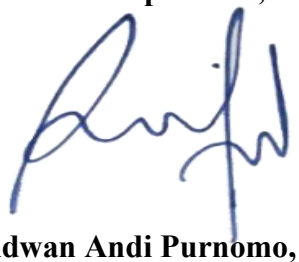
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DEDICATION PAGE

This thesis is dedicated to all of my family especially my mother Weti Roswiati and my father Muhammad Ramli that has been giving me their utmost support throughout the entire process of my college life. Furthermore, for all of my friends who have been around and pushing me forward this whole time.

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MOTTO

“Our greatest weakness lies in giving up. The most certain way to succeed is always to try just one more time.”
-Thomas Alva Edison

“It does not matter how slowly you go as long as you do not stop.”
-Confucius

PREFACE

Assalamu'alaikum warahmatullahi wabarakatuh.
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The final project is one of the requirements that must be fulfilled to obtain a bachelor's degree in industrial engineering from Universitas Islam Indonesia. Through the completion of this final project, the author has gained a deeper understanding of how the knowledge acquired during the course of study can be applied to scientific research.

In the preparation of this final project, the author received a great deal of guidance and support from various parties, both directly and indirectly. Therefore, the author would like to express sincere gratitude to:

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ABSTRACT

For Batik production, specifically in the textile manufacturing industry, the reliability of machine maintenance is crucial for assuring production process continuity. Scheduled preventive maintenance and reactive corrective maintenance, two traditional maintenance strategies, are commonly used in manufacturing but often result in inefficiencies such as early, unneeded maintenance and late response after failure occurrence. Responding to said problems, this research aims to develop a predictive maintenance optimization model for Batik printing machine using deep learning techniques. Both Long Short-Term Memories (LSTM) and Gated Recurrent Unit (GRU) models were used and combined into a hybrid model to forecast the Remaining Useful Life (RUL) of the Batik printing machine. Of 100 maintenance check datasets collected, 80% were used for training data, while the remaining 20% were used for testing data to then produce the predicted RUL. The RUL predictions were then analyzed to determine the optimal safe buffer, which is the number of hours at which maintenance should be proactively performed before predicted failure. In account for predictive, corrective, and preventive maintenance scenarios, different values of safe buffer ranging from 16 to 30 hours were tested to identify the exact point that minimized the total maintenance costs. Based on the findings and applying the optimal safe buffer, it leads to an efficient maintenance strategy consisting of 136 maintenance actions with varying yet specific strategies for each maintenance action. This integrated approach demonstrates that predictive maintenance, supported by RUL predictions and optimal safe buffer, can prominently enhance both the operational reliability and cost efficiency of Batik printing machines, suggesting a practical alternative to traditional maintenance planning.

Keywords: Predictive Maintenance, Neural Network, LSTM, GRU.

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CHAPTER I
INTRODUCTION

1.1 Background

In recent years, the industrial revolution has been rapidly growing each year, making the necessary for companies to have the ability to respond in respect of the growth. The revolution affects many kinds of industries, especially in terms of their development and economic growth. One of the impacted industries is the manufacturing industry where even more so, now, the industry is now pushed to be more efficient, flexible, and responsive to the changes that are happening. While there are many ways to achieve the desired efficiency, flexibility, and responsiveness, this thesis will focus on a specific problem regarding the maintenance of machines by means of prediction while considering the optimization for it to be more reliable than traditional maintenance methods. The proposed method is brought up as it has the potential to enhance decision-making and management in the targeted industry, which is the garment industry, specifically Batik.

The batik industry in Indonesia has always been a big part of its citizens' lives with big historical value that dates back to the 7^{th} century. The traditional art of Batik was recognized by UNESCO as part of Intangible Cultural Heritage in 2009, which triggered a big development for the Batik industry, making Batik one of the pillars of the economy in Indonesia (Wiradinata et al., 2023). Batik industry stands as the economic pillar for the citizens as it opens up a huge employment opportunity due to Batik's many applications starting from clothing and accessories such as bags, scarves, and even just the fabric sheets. Adding to the fact that Batik comes in many variations depending on the place of origin, the maker, and the technique used in the production of Batik to create different motifs that serve as an identification for what kind of Batik they are supposed to be. Some of the widely known and popular Batik motifs are the Sogan motif from Solo, Kraton motif from Yogyakarta, Mega Mendung motif from Cirebon,

and many more, with each of them being known as the Batik icon of the region (Febriani et al., 2023).

Traditionally, the creation of Batik is mostly handmade directly by people using some special techniques and tools. While sometimes traditional Batik takes a certain amount of time to be made, where a sheet of Batik fabric can take weeks or even months to be made, it is done to ensure the high quality of the Batik. The amount of time and effort thrown into the Batik creation directly by people's hands is the reason why traditional Batik tends to be more expensive compared to modern Batik. On the other hand, Batik creation in modern times strives to put out more quantity of Batik to make it readily available for the people and their demands. Manufacturing companies, most Batik garment manufacturers, use the help of machines in an assembly line to have a higher amount of output that is efficient in time yet consistent in quality. As a result, while the pattern of Batik is much simpler compared to those that are hand-drawn, modern Batik is generally cheaper and easier to find (Shaharuddin et al., 2021).

While it is true that modern Batik manufacturing with machines helps a ton with the popularization of Batik to be more common and easily obtainable for every person in Indonesia, it also has its own setbacks in the industry. PT. X in Pekalongan is one of the modern Batik manufacturers that deal with modern Batik manufacturing. The company relies heavily on the big machines that they have in order to have an output that meets people's demands. As it goes with every kind of machine, there are times when they break down and need special care to be repaired or maintained. If these kinds of problems are sidelined, then they can be harmful to the overall production capability of the company. There are many ways to act against these problems such as having regular maintenance of the machines.

However, there are several ways to conduct maintenance such as preventive maintenance, where tasks are scheduled to prevent failures from occurring, reactive or corrective maintenance, which is done after a problem arises with the machines, and timely maintenance that is done at regular intervals. Generally, according to Winter (2024), preventive maintenance is the most adopted method, followed by reactive maintenance in the industry world. One more type of maintenance that is less popular compared to the other two is predictive maintenance which predicts when the machinery is likely to fail using data analysis.

PT. X in Pekalongan adopted only a preventive strategy for the Batik printing machine maintenance. Although it is a good method, there are still some disadvantages, such as creating unnecessary downtime during the production process by conducting preventive maintenance

on the machine regardless of its current condition and wasting resources by changing functional parts that are not necessarily in a condition where they needed to be changed. Overall, these issues highlighted the disadvantages of maintenance using only preventive strategies, especially in terms of increasing time and cost where both are crucial components in a manufacturing company for achieving an effective and reliable production process.

Based on the previous issue of having only a preventive strategy for machine maintenance, this study will propose the idea of adopting predictive maintenance as an answer to the previously mentioned disadvantages. Predictive maintenance, at its core, is a maintenance strategy that mainly concern about the actual or current condition of the machine which means that the maintenance that is conducted under this strategy only occurs when it is truly needed, providing advantages such as avoiding premature part changes, giving early warnings that may help prevent major breakdowns, and timewise, the number of occurrence for predictive maintenance is generally lower than preventive maintenance (Achouch et al., 2022). Hence, there is an opportunity for the company to adopt the predictive maintenance method to increase their productivity while also lowering the cost in the meantime.

To conduct predictive maintenance on the Batik printing machine, historical data from the company will be used in a time series forecasting, using data and analytics to predict when machine failures are more likely to occur. In time series forecasting, however, it is important to note that the data will be sequential data that has to be handled correctly. In terms of handling sequential data, Neural Networks, specifically Recurrent Neural Networks (RNNs), are one of the best options, as simply said, RNNs have something called a hidden state or internal state, which is an important component that allows the network to capture and retain information from previous inputs, allowing RNNs to process the sequential data (Weerakody et al. 2021). One downside to RNNs is the difficulty of learning long-term dependencies in data, also known as the vanishing gradient problem. To answer this problem, a specifically designed concept is needed which is the Gated Recurrent Architectures. The concept can also be further divided into several types, each with its own functionality, such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU).

Both LSTM and GRU are similar concepts under the Gated Recurrent Architecture, where the two control the flow of information in the networks. The former, LSTM, has three gates that can be divided into input, output, and forget gates, while the latter, GRU, only has two gates, which can be divided into reset and update gates. In terms of complexity, LSTM is

generally more complex, which makes it more expensive computationally compared to GRU, which is simpler and requires less time in its training due to its relatively simpler architecture. Performance-wise, however, LSTM serves better on longer sequences compared to GRU, which can sufficiently serve simpler sequences (Nosouhian et al., 2021). And, with the collaboration of the two concepts, it is possible to cover both concepts' disadvantages and create a better approach for predictive maintenance.

Before the procession of predictive maintenance, the historical data collected will be used to find important information about the machine, called the Remaining Useful Life (RUL). As the core concept within the study, RUL is the value calculated from the collected machinery data, such as temperature, load units, and last maintenance data, that shows the remaining time that the machine has for production before it is likely to experience a failure or breakdown. In this study, historical RUL data will be processed in a hybrid model by using LSTM layers to capture the long-term dependencies within the data, after then it is sent to GRU layers to refine the found patterns while focusing on the short-term dynamics, which finally produces results in the form of predicted RUL.

Finding the predicted RUL is not the end goal of the study; there is a need for an optimization to find out about the optimal safe buffer for the Batik printing machine. The optimal safe buffer is the exact time within the RUL where, at that point, the machine maintenance should be proactively performed before any kind of failure occurs. The optimization will utilize the predicted RUL and machine cost data to calculate the threshold of which shows the exact point where the cost is at its lowest while also having the optimal time for maintenance, not too often and not too seldom.

By relying on the methods mentioned above, it is targeted that through the research, predictive maintenance can offer a new reliable maintenance strategy that is more cost and time-efficient for the Batik manufacturing company to increase the overall efficiency of the company's production process.

1.2 Problem Formulation

In the garment industry, including Batik printing, machine reliability and maintenance efficiency are crucial to ensuring operational continuity and production quality. Traditionally, maintenance in this kind of industry is done by preventive and corrective measures. In the former, preventive measures, machines are maintained at certain intervals without caring about their actual condition. While it certainly reduces the possibility of unexpected failures, it has

the issues of inefficiencies in using resources, the occurrence of unnecessary maintenance activities, and increased downtime. The latter, corrective measures, are conducted after a machine has already failed which resulting in higher costs due to the production loss, defects in quality, and emergency repair.

With the development of industry in recent years, there has been an alternative to machine maintenance, which focuses on the actual condition of the machine, called predictive maintenance. It gathers the machine's actual data by utilizing sensors within the machine and the historical operation data of the machine before then processing the data collected using machine learning techniques to estimate things such as Remaining Useful Life (RUL), which in the end, enables maintenance to be conducted only when the machine condition is actually in need of maintenance. However, most existing studies focus more on the improvement of RUL prediction accuracy instead of translating the predictions into solid decision-making frameworks. This leads to a gap in determining the optimal timing at which predictive maintenance should be proactively conducted in order to minimize the total costs, or the so-called safe buffer. The safe buffer then serves as a balance for the trade-offs between conducting maintenance too early, which results in excessive and unnecessary costs, or too late, which results in failures and corrective costs.

To answer this gap, this research develops a cost-optimization model based on RUL predictions generated by a hybrid Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) neural network. It is applied to real Batik printing machine operational data to determine the most cost-effective threshold for the trigger of predictive maintenance activities.

Based on the previous explanation, there are two problems formulated as follows:

1. What is the optimum period for predictive maintenance to be conducted in order to avoid excessive or costly maintenance of other maintenance strategies?
2. Can predictive maintenance using LSTM and GRU models improve overall efficiency and minimize total maintenance costs of the Batik printing machine?

1.3 Research Objectives

The research objectives answer the formulated problems. The following are the objectives of the research:

1. To determine the optimal period for when predictive maintenance should be conducted on Batik printing machines.

2. To investigate the effectiveness of predictive maintenance using LSTM and GRU models in improving overall efficiency and reducing the costs of Batik printing machines.

1.4 Benefits of Research

Benefits of the research for the students:

1. The research will help students gain experience in conducting academic research, writing a thesis, and contributing to their field of study.
2. The research provides students with practical experience in applying theoretical knowledge to solve real-world problems in a manufacturing setting.

Benefits of the research for the university:

1. The research will contribute to the university by adding to the knowledge base in the fields of data analytics, manufacturing, and supply chain management.

Benefits of the research for the company:

1. The research findings can provide the company with a competitive edge in the market by enabling better decision-making and more responsive supply chain management.
2. The research will help the company make better use of its existing data, transforming it into actionable insights that can be used for strategic decision-making.

1.5 Research Limitations

There are several limitations to the research to serve a better overall focus of the research:

1. The proposed predictive maintenance system heavily relies on the availability and accuracy of the collected data, making inconsistencies that impact the predictive maintenance model's ability to provide actionable insight.
2. With the subject specified to one Batik garment company, the results and the predictive maintenance may not be universally applicable across different industries since they might have different needs or requirements.
3. While a predictive maintenance model might be proven effective, users' ability to adopt and use the system efficiently is also a consideration, causing the use of appearance for a learning curve associated with the tools may require users to spend some time adapting.

1.6 Systematic Research

Systematic research is the portrayal of content of the thesis which is divided into six main chapters as follows:

CHAPTER 1 INTRODUCTION

This chapter explains in general the background of the research, problem formulation, research objectives, benefits of the research, and research limitations.

CHAPTER 2 LITERATURE REVIEW

This chapter contains reviews of previous research with similar themes to the current thesis. The chapter is then divided into two sections, deductive study and inductive study, with the former being a literature review of research to find the gap for the current thesis and the latter being a theoretical basis that explains the terms in relation to the topic of the thesis.

CHAPTER 3 RESEARCH METHODOLOGY

This chapter explains the methods that will be used in the thesis, starting from the subject and object of the research, the data collection techniques, to the flow diagram of the thesis progression.

CHAPTER 4 DATA COLLECTION AND PROCESSING

This chapter discusses the collected data that has been obtained before processing the data in accordance with the selected methods to achieve output that can be used to answer the objectives of the research.

CHAPTER 5 DISCUSSION

This chapter contains a discussion regarding the whole research that has been done to prove whether the conducted research answers the problem formulated in the thesis or not.

CHAPTER 6 CLOSING

The last chapter is divided into two parts: conclusions and suggestions. The conclusions are briefly about the conducted research and the answers to the research questions. Suggestions include the opinion of the writer in regard to the improvement that can be made and the drawbacks in the thesis that can be avoided for further studies.

BIBLIOGRAPHY

APPENDIX

CHAPTER II
LITERATURE REVIEW

2.1 Theoretical Basis

There are several theoretical bases related to the research such as the following:

2.1.1 Industrial Revolution

As humanity has advanced in the past few hundred years, there is one sector that has heavily affected how society lives, along with its development, which is the industrial sector. Industry has always been striving to improve human lives by creating convenience to answer the problems that humans face over time. A book by Allen (2017) briefly describes the changes of the industrial revolution throughout history, which can be divided into the following:

1. The First Industrial Revolution

   The first industrial revolution occurred in the late 18^{th} to early 19^{th} century. There are several key innovations during that time, such as steam engines, mechanization, and the use of water and steam to generate power. The biggest impact of this revolution is the transition of human society, which used to rely on hand production, into machines, leading to the rise of factories and bigger production.

2. The Second Industrial Revolution

   The second industrial revolution occurred in the late 19^{th} to early 20^{th} century. Some innovations, such as electricity and the assembly line, emerged as two important improvements in the industrial sector since the introduction of these two enabled mass productions, expanded the steel, chemicals, and railroad industries, and revolutionized the manufacturing sector.

3. The Third Industrial Revolution

   The third industrial revolution occurred in the middle of the 20th century. The revolution introduced digital technology, computers, and automation, which caused the shift from mechanical and analog processing to digital technology. The rise of computers and electronics at that time led to the globalization of manufacturing.

4. The Fourth Industrial Revolution (Industry 4.0)

   The fourth industrial revolution emerged in the 21st century and has been in development up until now. It began with the introduction of the internet, which then further developed into concepts such as the internet of things (IoT), big data, and artificial intelligence (AI). The biggest impact that Industry 4.0 has is the integration of digital, physical, and even biological systems in industries, which leads to the achievement of smart factories, enhanced automation, and real-time data analytics. Along with its development previously and in the future, Industry 4.0 tries to emphasize connectivity, data-driven decision making, and advanced manufacturing technologies.

In the meantime, companies, including those that dwell in the manufacturing industry, strive to improve their future development following the changes in Industry 4.0. However, some manufacturing companies are found to face challenges in the way of their development, especially in the aspects of cloud computing and services, internet of things (IoT), big data, and analytics (Frank et al., 2019). Only when the companies can overcome these challenges, the benefits of Industry 4.0 be fully realized. The benefits will then be essential for companies to adapt and innovate, ensuring that they will remain competitive in the increasingly complex and competitive global market.

2.1.2 Supply Chain Management

In a manufacturing industry, one of the most critical components is supply chain management, which is a business strategy that cannot be overlooked by companies as it encompasses the collaboration and management of a network of interconnected parties involved in providing goods and services to end-users. According to Wisner et al. (2021), supply chain management aims to integrate supply chain activities, including procurement, production, distribution, and logistics, to achieve a better flow of information, products, and finances. It is also mentioned that in order to create an effective supply chain management system, a broad approach considers all stakeholders' goals, enhances collaboration, and uses technology to improve visibility and responsiveness across the supply chain activities.

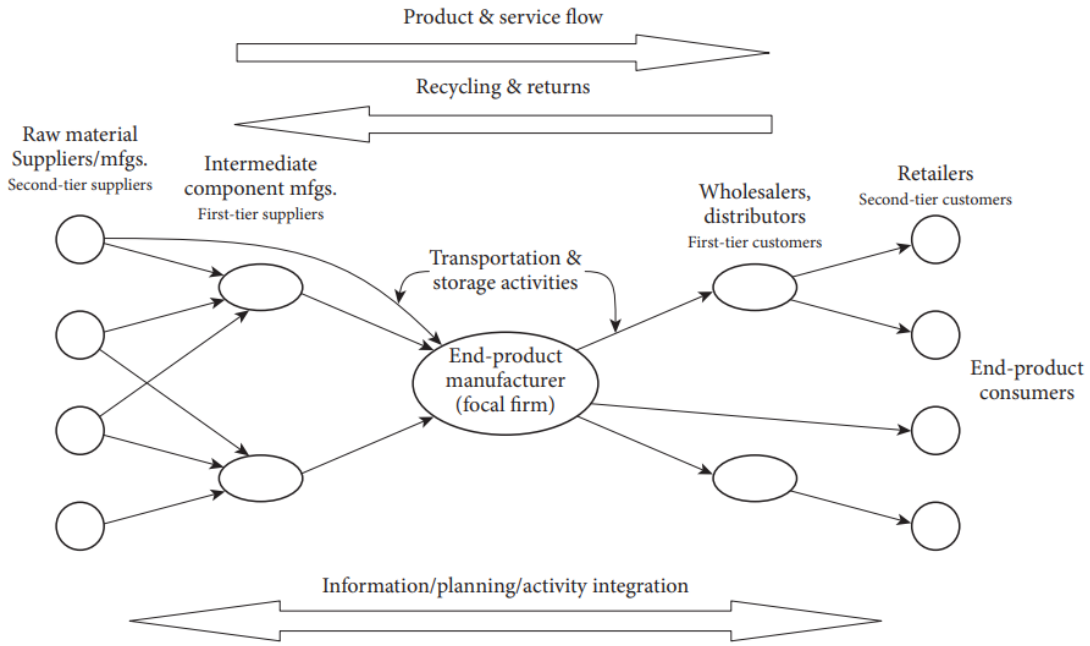


Figure 2.1 *General form of a supply chain activity*

Source: (Wisner et al., 2021)

As time passes, supply chain management has experienced advancement from adopting digital technologies in the practices, which then revolutionized how supply chain activity operates. Now, it is easily possible to track goods throughout the supply chain and to provide real-time information on location, condition, and status of goods during the shipment process. This shows the increase in visibility, which enables companies to respond quickly to unexpected disruptions, optimize inventory levels, and reduce lead times. Using a more efficient and resilient supply chain management, companies will be able to have more accurate forecasting and demand planning and enhance their decision-making processes.

2.1.3 Machine Condition Monitoring

Modern manufacturing industries often rely on machinery in most parts of their production process. The machines contribute massively to the amount of production and the time spent on production in a company. Contrary to the benefits the machines bring, they also need some special care to ensure that all the machines are working properly. As an answer, companies may implement the practice of machine condition monitoring. Correa and Guzman (2020) elaborated that machine condition monitoring is a practice that focuses on real-time assessment of machinery health, which is then used to predict machine failures and optimize the maintenance schedules. The assessment then helps in identifying early signs of machinery

problems, such as wear and tear, allowing for appropriate response or intervention before the occurrence of catastrophic failures.

According to them, there are several key techniques that are used for machine condition monitoring, with each having different places in which they can be applied. Some of these techniques are as follows:

1. Vibration Analysis

   This technique is one of the most commonly used for machine condition monitoring. It relies on the fact that the machine vibrates during the production process, and the normal rate of vibrations is recorded as the standard. When there is any sign of deviation from the normal rate, it may indicate errors in the machine, such as misalignment, imbalances, bearing failure, and so on. The vibration analysis method will use sensors attached to the machines to capture the vibration, with the feedback being data that can be analyzed to identify the potential problems before they lead to machine breakdowns.

2. Thermography

   Thermography is a monitoring technique that uses temperature data of the machine components. It uses infrared cameras to detect temperature variations like overheating in parts such as motors, bearings, and electrical components. In its practice, thermography is most useful in monitoring electrical systems, wherein raised heat can easily occur and then cause hot spots, which may indicate overloading or insulation failure.

3. Oil Analysis

   Speaking of machinery, oil is one part that cannot be missing in order to make the machines work perfectly. It requires regular analysis to see whether there are any contaminants, metal particles, or changes in viscosity that may lead to the degradation or contamination of the oil. When there are signs of those issues, maintenance in the form of oil changes needs to be done by the maintenance team, and if there are any abnormal issues in the oil, then there will be a need for further investigation.

4. Ultrasound Monitoring

   In some cases, there are changes happening in machinery that cannot be clearly heard by human ears, leading to a need for technology that can monitor it, which is ultrasound technology. It is a technology that is used to detect high-frequency sounds emitted by the working machinery to provide additional data on machine health that may complement other

machine condition monitoring techniques. It is particularly effective in identifying leaks in compressed air systems, detecting electrical discharges, and monitoring bearing conditions.

2.1.4 Data Analytics in Manufacturing

Considering that technology has become more and more digitalized these days, manufacturing companies also could not help but follow this digitalization initiative. By digitalizing the company data, it will make it easier for them to utilize the data compared to the traditional methods. However, proper handling of data is required to make it useful, as mishandling will make the collected data become useless or misinterpreted instead, and one of the ways to properly handle data is by having data analytics. Data analytics has become an essential tool in manufacturing, enabling companies to harness immense amounts of data to improve efficiency, quality, and decision-making.

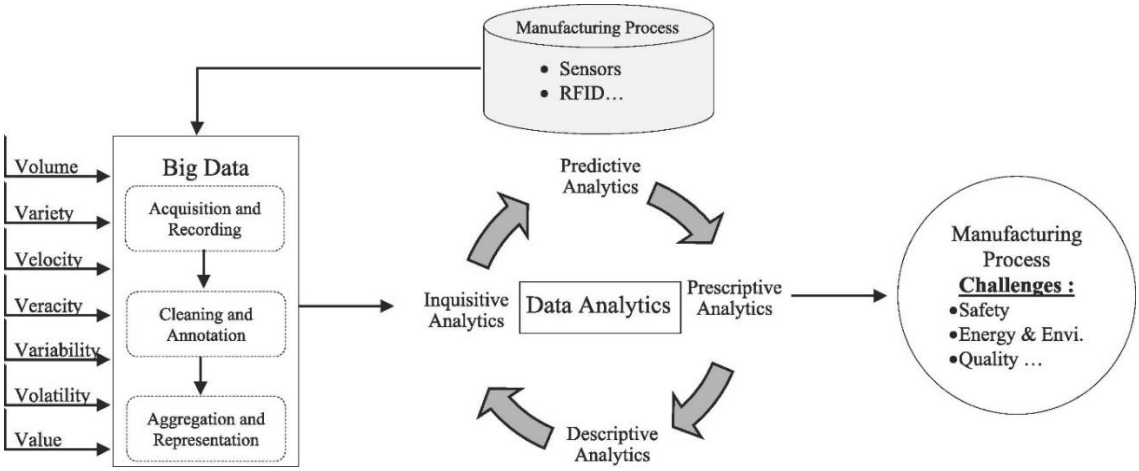


Figure 2.2 *Data analytics in the context of the manufacturing industry*

(Source: Belhadi et al., 2019)

According to Belhadi and his friends (2019), data analytics in the manufacturing process can basically be divided into four stages, in order, they are as follows:

1. Descriptive analytics

   Descriptive analytics is all about the summarization of historical data to provide insights into past performance. In the manufacturing context, it involves analyzing production data, quality reports, and machine performance logs to understand trends and identify areas for improvement. It also provides a clear view of what has happened in the past so that manufacturers can understand patterns in machine utilization, production delays, or quality defects. As it is mostly about what happened in the past, descriptive analytics becomes the first of the four as the starting point, which is to focus on understanding and summarizing historical data.

2. Inquisitive analytics

   Inquisitive analytics is also known as diagnostic analytics, which has the role of uncovering the root causes behind specific trends or outcomes. One example in the manufacturing context is that if a manufacturing line experiences an unexpected decrease in production efficiency, inquisitive analytics would delve into the data to determine the reasons behind the dip, such as operator errors, machine malfunctions, or supply chain disruptions. It becomes the second of the four as after understanding the past, inquisitive analytics helps to investigate why certain things happened.

3. Predictive analytics

   Predictive analytics utilizes collected historical and real-time data, along with statistical models and machine learning algorithms, to predict future outcomes. In the manufacturing context, predictive analytics helps to prepare against production bottlenecks, potential equipment failures, and demand fluctuations. It also helps optimize inventory management by predicting material shortages or overstocking based on historical consumption patterns. It is the third of the four, as once the reasons behind past trends are clear, predictive analytics uses that information to forecast future outcomes.

4. Prescriptive analytics

   Prescriptive analytics is more than just predicting outcomes, as it suggests specific actions to achieve desired results. In a manufacturing context, prescriptive analytics recommend optimal actions by analyzing data from various sources, such as production systems, supply chain, and machine performance. In one example, if a predictive model shows that a machine is likely to fail, prescriptive analytics suggest the best choice of action, which is whether to perform maintenance immediately, wait until the next shift, or reroute production to other machines to minimize downtime. It is the last of the four as it provides appropriate strategies to optimize outcomes after predicting future scenarios.

2.1.5 Maintenance in Manufacturing

The manufacturing industry is no stranger to maintenance, with all the machines and facilities within the industry being subject to maintenance most of the time due to the frequent and regular use in production. It is a crucial issue to have maintenance as it helps with productivity in the long run by enabling the machines or facilities to run smoothly. If there is no presence of maintenance within the industry, not only can it reduce productivity, but it can also shut down the industry entirely, since production cannot be continued with broken machines or facilities.

According to Winter (2024), maintenance in the industry world can be divided into the following:

1. Reactive Maintenance (Maintenance 1.0)

The reactive maintenance is done only when or after a failure occurs. It has the advantage of being simple to implement and having no upfront cost. However, the disadvantages are also obvious, starting with unplanned downtime and high repair costs. This strategy is most suitable for equipment that is non-critical and when the failures have minimal to no impact on the whole operation.

2. Preventive Maintenance (Maintenance 2.0)

Preventive maintenance is done regularly by having scheduled maintenance based on time or usage of the machine or facility to prevent failures from occurring. It reduces the risk of failure and increases the asset's life, but there is a big chance of over-maintenance while also not reflecting the actual equipment conditions. This strategy is most suitable when equipment is expensive, critical, and prone to failure.

3. Predictive Maintenance (Maintenance 3.0)

Predictive Maintenance is done by utilizing sensors to monitor equipment to perform condition-based maintenance based on the actual condition of the machine. The advantages come with the reduced downtime due to the real-time monitoring and having maintenance only when necessary. The disadvantages, however, come with the higher cost of setup, such as the sensors and the requirement for skilled personnel who can operate the predictive maintenance itself.

2.1.6 Predictive Maintenance

After having monitored the machine conditions and considering the data analytics methods, predictive maintenance can be done in accordance with the machine situation. Regular or preventive maintenance is widely used by companies to take care of their machines; however, with sufficient technology, companies can also perform predictive maintenance instead. The difference between the two is that the former occurs at predetermined intervals, like once per two months, while the latter occurs depending on the actual condition of the equipment as monitored, which means every time there is a sign of problematic issues found within the machine. Implementing predictive maintenance in a company may reduce unnecessary maintenance, minimize downtime and cost, and extend the lifespan of machinery.

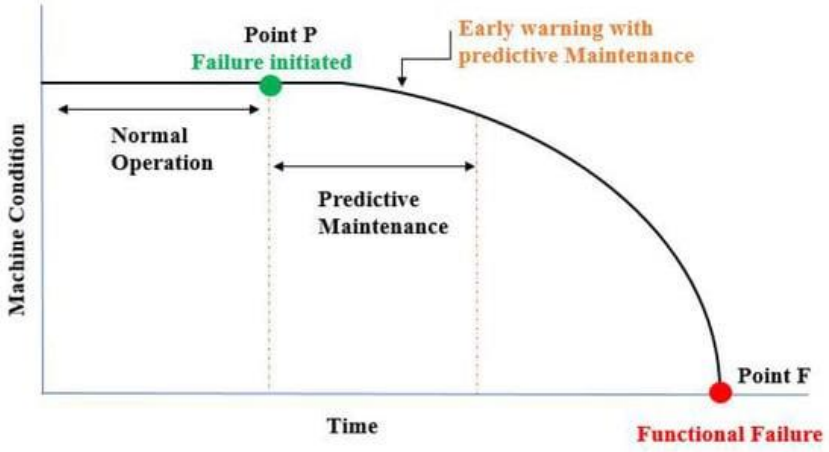


Figure 2.3 *Potential failure and predictive maintenance diagram*

(Source: Achouch et al., 2022)

As shown in the figure, predictive maintenance offers the highest reliability and longest life of equipment. In its core, it utilizes various monitoring technologies and data analysis techniques to collect data. The data collected from these technologies is then processed using algorithms and machine learning models to predict the likelihood of equipment failure. To make it even more accurate, historical and real-time data may be integrated to identify patterns and abnormalities that may indicate future problems (Achouch et al., 2022). With sufficient information provided by the monitoring, it allows timely intervention in case of unseen changes, enabling companies to minimize downtime and avoid costly repairs.

The issue with predictive maintenance is the real implementation of the predictive maintenance system in the company itself. Companies without the necessary components will not be able to implement it correctly, especially in the first phase of implementation, as it requires a lot of initial cost and the ability to handle the complexity of the predictive systems. The costs are not only going for the sensors and other equipment required for prediction and maintenance, but also going for investment in people to make them become skilled personnel capable of running the predictive maintenance system. Thus, it will be easier for a newly emerged company to implement it compared to an industry with legacy equipment, where they may struggle since it necessitates substantial upgrades or modifications to existing systems.

2.1.7 Time Series Forecasting

In relation to prediction, one particular technique to estimate the possible outcome at certain times is time series forecasting. In its definition, time series forecasting is a practice or technique that is commonly used to predict future values based on past data by analyzing the patterns, trends, or seasonality that appear in the historical data. Practice generally involves

some kind of statistical tools or machine learning models to make predictions. Time series forecasting is widely popular for weather forecasting, stock prices, or sensor readings with all of which are fundamentally data points that are recorded over a certain period. According to Peixeiro (2022), a time series has its own components that can be divided into the following:

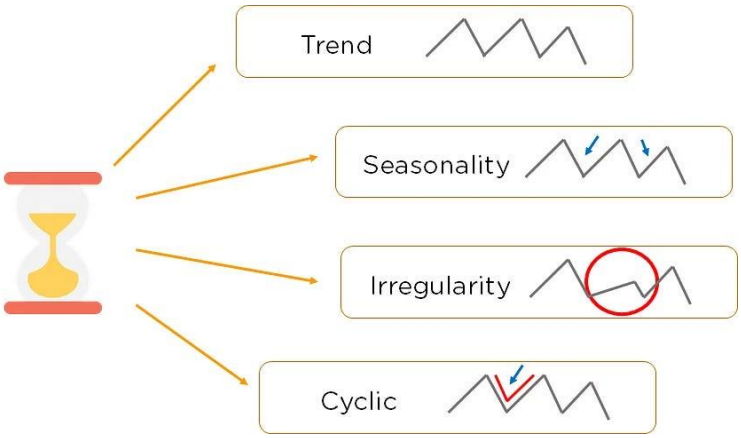


Figure 2.4 *Components of a time series*

(Source: Medium)

In accordance with the figure above, the basic key components of a time series can be explained as follows:

1. Trend

   A trend is a component of a pattern in a time series that appears over a long period. Depending on the data, a trend can come in three forms starting with an increasing long-term pattern called the upward trend, a decreasing long-term pattern called the downward trend, and a pattern that neither exhibits an increase nor decrease in the long term called the stationary or horizontal trend.

2. Cyclical

   Cyclical components can be identified as the cycles or irregular fluctuations around the overall trend. Cyclical patterns generally last longer than a seasonal pattern, being a year or even more, while also being inconsistent for their period of occurrence. An example that can be seen regularly is in the business cycle, where there are events such as an economic recession or recovery.

3. Seasonal

   Seasonal components appear when there are regular fluctuations in a time series. The regular pattern generally appears during the same period every year. Seasonality can be commonly seen in a holiday season, such as The New Year and Ramadhan in Muslim countries.

4. Irregular

   Irregular components are something that is usually called a random variable in a time series. It is unpredictable and often left unexplained within a time series. Furthermore, irregular components are relatively short-lived compared to the other three components mentioned previously.

In a study by Liu and his colleagues (2021), it is explained that there are several methods or techniques commonly used for time series forecasting, some of which are as follows:

1. Moving Average

   Moving average is a simple forecasting technique that identifies patterns by observing past data to find the average of a fixed amount of data. For example, in a moving average with three months as the fixed number, it means that to forecast the next month's value, it will be equal to the average of the past three data points.

2. Exponential Smoothing

   Exponential smoothing is a technique that is very similar to the moving average technique. It also uses several past data points with a fixed number, such as in the last four months, but with more emphasis on the more recent data. The emphasis is given in the form of weights that are added to the past data, where the more recent the data is, the more weight it will have.

3. Deep Learning

   Deep learning is a more complicated and relatively newer technique in time series forecasting compared to the previous two. Using deep learning by taking advantage of machinery, the technique depends on algorithms that study historical data and make a new solution based on it. The benefit of the technique is that it offers more flexibility and can capture complex patterns in the data. Some of the deep learning methods include Recurrent Neural Networks (RNNs), Transformers, and XGBoost.

2.1.8 Recurrent Neural Networks (RNNs)

Recurrent Neural Networks are one type of neural network that has been developed and used over the years alongside Feedforward Neural Networks (FNN), Convolutional Neural Networks (CNN), Transformer, and others. Neural networks itself is a computational model that is inspired by how a human brain works such as its structure and function. Neural networks are composed of nodes or neurons that are interconnected with each other in layers, which then

process data by simulating how actual neurons work (Taye M., 2023). Generally, the layers can be divided into three main types as follows

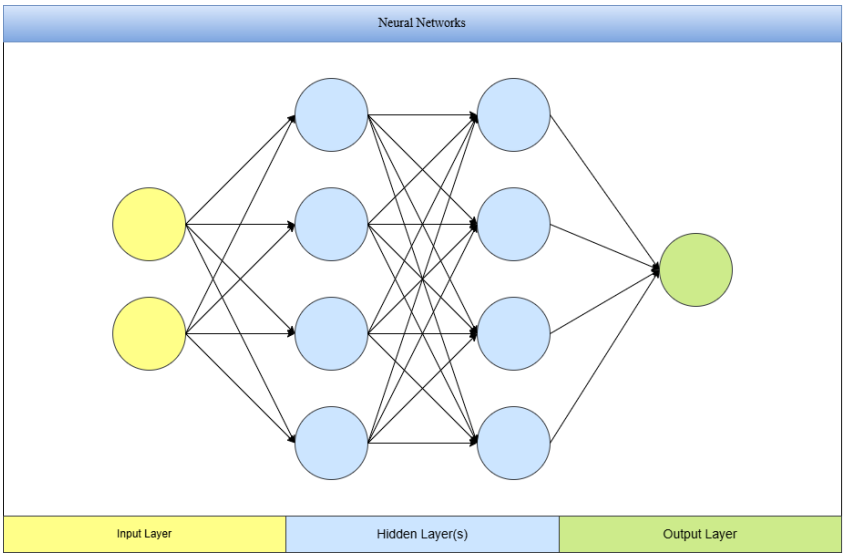


Figure 2.5 *Basic Neural Networks model*

1. Input Layer

   Responsible for receiving new data.

2. Hidden Layer(s)

   Responsible for processing data by using weighted connections.

3. Output Layer

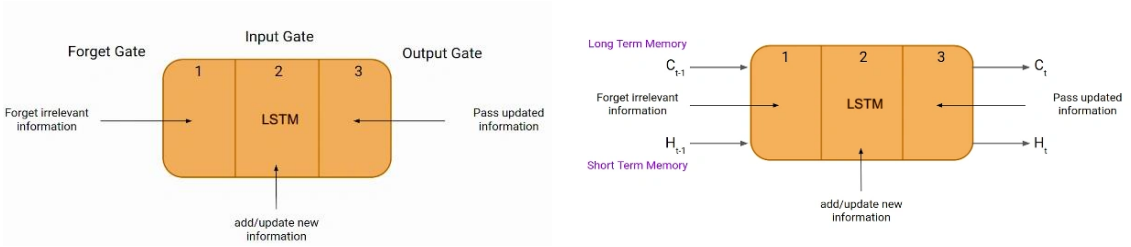
   Produces the final predictions.

Recurrent Neural Networks (RNNs) generally have a similar purpose as their predecessor, Neural Networks, which is a computational model that processes data but with a more specific design for sequential data where RNNs use outputs from previous steps as inputs to the current steps, holding the previous inputs as memory in a hidden state which is important for tasks that concern about the order where it may affect the outcome (Das S. et al., 2023). Sequential data is data where context and order are important, such as in time series, speech, or other texts.

Running Recurrent Neural Networks (RNNs) does not necessarily come without any kind of problems. The most common occurrence of issues around RNNs is the vanishing gradient problem, an occurrence that happens as the sequence of data gets longer and longer which results in the network being struggling or even unable to learn long-term dependencies. Some methods have been developed to answer the issue such as Gated Recurrent Architectures that can be further divided into Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU).

2.1.9 Long Short-Term Memory (LSTM)

A special kind of Recurrent Neural Networks (RNNs), one of the types of Gated Recurrent Architectures that answer vanishing gradient problems, Long Short-Term Memory (LSTM) is designed to learn long-term dependencies in sequential data. For its application, it is mostly used for time series prediction, language modeling, and speech recognition. The components or architecture of LSTM consist of several gates and states, the division, according to Saxena (2025), can be seen in the following figure.



(a) (b)

Figure 2.6 *(a) LSTM gates (b) LSTM states*

(Source: Analytics Vidhya, 2025)

1. LSTM gates

   LSTM gates, with the function of controlling the flow and transformation of information in the network, are divided into three parts following figure (a).

   a. Forget gate

   The forget gate has the function of deciding what past information should be removed from memory hence preventing irrelevant data flowing through the network.

   b. Input gate

   The input gate has the function of determining what new information should be added to the memory, hence updating the network with fresh and relevant information.

   c. Output gate

   The output gate has the function of controlling what information from the cell state is produced as output, which could be used to influence the next layer in the network.

2. LSTM states

   LSTM state, with the function of storing information regarding the sequence during data processing to influence current and future outputs, is divided into two parts following figure (b).

   a. Hidden state

Also known as LSTM's short-term output memory, which is generally used as the next input or to generate predictions.

b. Cell state

Also known as LSTM's long-term memory, which carries accumulated information across several steps within the network, preserving relevant information with minimal changes.

2.1.10 Gated Recurrent Unit (GRU)

The other type of Gated Recurrent Architecture is Gated Recurrent Unit (GRU). Compared to the other type, Long Short-Term Memory (LSTM), GRU is simpler in terms of its structure but has a similar design, which is to handle sequential data. The components or architecture of GRU consist of several gates and states; the division, according to Mohsen (2023), can be seen in the following figure.

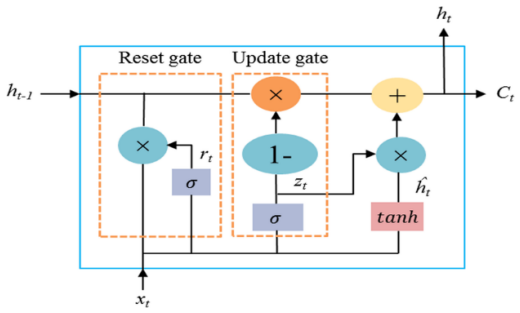


Figure 2.7 *GRU architecture*

(Source: Shiri et al., 2023)

1. GRU gates

   GRU gates are divided into two parts.

   a. Update gate

   Update gates have the function of controlling which hidden state from the previous step is stored, contrary to new updated information, basically balancing old and new info in terms of forgetting and adding.

   b. Reset gate

   The reset gate has the function of determining which past information should be ignored when creating a new hidden state, helping the network to reset memory if necessary.

2. GRU states

   Unlike LSTM, GRU only has one state as follows.

   a. Hidden state

Different from LSTM, which differentiates between hidden and cell state, GRU merges both states into one single vector that gets updated at each step in the network. To further differentiate from LSTM, the hidden state of GRU is responsible for both short-term memory and long-term memory.

2.2 Literature Review

There are several literature reviews based on previous works or research related to the topics, some of which are as follows:

2.2.1 Predictive maintenance using LSTM models

Research on predictive maintenance by relying on LSTM models has been done on several scopes of study with differing research objectives. Some of these studies are as follows:

In the first study done by Bampoula, Siaterlis, Nikolakis, and Alexopoulos (2021), a cyber-physical production system was observed, and it was found that the system maintenance can be improved to be more effective by using predictive maintenance through combining monitoring with machine learning. To obtain data required for predictive maintenance without a destructive approach, the study used a method where previous preventive maintenance with predetermined schedules is transitioned into predictive, making the maintenance operation more focused on the actual operational status. For the approach, LSTM autoencoders were developed as a prototype to estimate the remaining useful life of the equipment after the application of an autoencoder-based method to classify machine and sensor data. Lastly, in a case related to the steel industry production process, the proposed approach was validated.

The second study by Hu, Wang, Tan, and Cai (2023) focused on the issue of indoor climate control in the building industry, as it was found that failure prediction is a complex challenge that remains within the issue. The study addressed the issue by combining both supervised and unsupervised learning using the integration of remaining useful life and time shift methods, calling the proposed solution a digital twin-enabled framework. In the approach, LSTM and autoencoder techniques were fused into a hybrid prediction model, where the hybrid was then applied to real-world indoor air quality from buildings in Singapore. It is obtained as the result that the model outperformed four benchmark algorithms that had been predetermined, particularly for low-severity failures, where it achieved almost 80% accuracy, which is around 10-15% higher than other benchmarks. It was also found during the validation through an interactive online platform that the proposed framework was able to demonstrate how digital twins can improve the implementation of predictive maintenance strategies in the building industry.

The third study that used LSTM for predictive maintenance was done by De Simone and his colleagues (2023). The study recognized that in order to minimize downtime and operational costs, effective maintenance is vital; it then targeted the rail system, where

degradation gradually happens, as the object of the study. As the methodology, an LSTM deep learning model was used to learn long-term patterns in slowly varying data of the rail degradation. While collaborating in an academic-industrial collaboration, a train traction converter cooling system capable of prediction was applied. The method resulted in over 99% accuracy in predicting and forecasting failures, demonstrating predictive maintenance potential for real-world railway maintenance optimization.

In the fourth study by Pagano (2023), it was highlighted that with the advancement of artificial intelligence in Industry 4.0, there is potential for the development of predictive maintenance. Using data from a company dealing in heavy industry, specifically from monitoring sensors installed within their plant, the study proposed a predictive maintenance to combine LSTM neural networks with Bayesian inference. In the data processing, the method was responsible for updating the probability of the plant being in a good working condition by using Hotelling's T^2 and Q metrics to evaluate deviations from normal operation. The resulting method was then applied to a real industrial plant as a specifically designed dashboard responsible for the company's maintenance after several tests were performed in which it was demonstrated to be effective in detecting early signs of deviation.

The fifth study, conducted by Kim and Choi (2021), focused on improving predictive maintenance by considering the choice of model, as it highlighted that predictive maintenance relies heavily on the accuracy of modeling machine health. LSTM network for predictive maintenance, optimized by an artificial intelligence-based approach, was proposed by the study specifically for machinery bearing components. A two-stage method was applied in the study, each brought specific improvement, with the first being the construction of effective health indicators (HIs) to accurately represent machine conditions and the second being the usage of Genetic Algorithms (GA) to optimize the hyperparameters of the LSTM model, enhancing its predictive performance. The study results showed the potential to improve predictive accuracy while also showing that it can be extended to other deep learning maintenance systems.

2.2.2 Predictive maintenance using GRU models

Research on predictive maintenance by relying on GRU models has also been done on several scopes of study with differing research objectives. Some of these studies are as follows:

The first study is a comparative study done by Sivakumar, Reddy, and Varma (2025). It was highlighted that GRU has advantages for real-time anomaly detection and failure prediction, but is also limited in terms of handling noisy data and long-term dependencies. A

comparative analysis of GRU against other deep learning architectures was conducted, and it was found that GRU models excel in speed and memory efficiency compared to LSTM models. The previous limitation of GRU models was also found, and it was indicated that there was a need for an additional solution, such as a hybrid model structure. To answer this problem, the study proposed a GRU-Transformer hybrid model, which improved its accuracy and robustness in complex environments. It is confirmed in the findings that GRU is most practical in time-sensitive applications, and hybrid approaches help GRU under challenging conditions to enhance its predictive performance.

The second study addressed challenges in data availability and model accuracy by proposing a novel method for the prediction of the remaining useful life (RUL) of bearings with small samples. It was done by Zhou, Qin, Chen, Liu, and Qian (2022). A method was used to minimize reliance on expert knowledge, where a Kullback-Leibler divergence (KLD)-based health indicator (HI) is constructed using a Gaussian Mixture Model (GMM). Reinforced Memory Gated Recurrent Unit (RMGRU) was then introduced in the study to improve long-term trend retention by reusing previous state information to improve forecasting. The experimental results showed RMGRU's superior accuracy compared to conventional RNN-based approaches, making it suitable to be applied in real-life predictive maintenance.

The third study was done by Zainuddin and Hasan (2021), which addressed the high dimensionality problem that occurred in the time series data with big data, specifically in the oil and gas sector. The proposed method for the study was a Recurrent Neural Network-Gated Recurrent Unit (RNN-GRU) model, which leveraged GRU's simplified structure and gate mechanism to efficiently handle data sequences, finally enabling real-time prediction for machinery health. The result showed an 87% accuracy, which highlighted the model's potential in preventing unplanned equipment failures, hence reducing costly disruptions in the whole operation.

The fourth study, done by Kaleli, Unar, and Ozer (2021), targeted the challenges faced in industrial environments with high-volume time-series sensor data, such as remaining useful life (RUL) and failure likelihood in predictive maintenance. The study introduced a GRU-based deep learning model capable of simultaneous prediction of both RUL and failure likelihood within a single architecture, which is still an unexplored area of multi-output, end-to-end modeling. It was experimented on NASA's benchmark predictive maintenance dataset, where

it showed that GRU not only significantly reduces training time but also matches or goes beyond the predictive performance of LSTM and other RNN models.

The fifth and last study was done by Zhang and his colleagues (2022), which aimed to replace subjective expert-based assessment with an unsupervised anomaly detection algorithm (DBSCAN) to develop a more objective yet accurate predictive maintenance method while also leveraging GRU's strengths. D-GRU, a combination of the GRU model and DBSCAN clustering, was introduced in the study as an approach to predictive maintenance responsible for assessing and forecasting industrial equipment systems' health status. DBSCAN, empowered by Chebyshev distance, was responsible for labelling historical operating data by detecting anomalies, whereas the GRU model was trained using the anomaly data to predict future abnormal states. The result of the study was proved effective in improving model performance as it demonstrated similar or better results compared with classical models referenced in the study.

Table 2.1 *State of Arts*

No.	Author, Year	Methods			
		Predictive Maintenance	LSTM	GRU	Optimization
1.	Bampoula, X., et al. (2021)	√	√		
2.	De Simone, L., et al. (2023)		√		
3.	Hu, W., et al. (2023)	√	√		
4.	Kaleli, A. Y., et al. (2021)	√		√	√
5.	Kim, D. G., & Choi, J. Y. (2021)	√	√		√
6.	Pagano, D. (2023)	√	√		
7.	Sivakumar, V., et al. (2025)			√	
8.	Zainuddin, Z., P. Akhir, E. A., & Hasan, M. H. (2021)	√		√	
9.	Zhang, J., et al. (2022)	√		√	
10.	Zhou, J., et al. (2022)	√		√	
11.	Mufarriji, M. L. A. (2024)	√	√	√	√

According to the state of the art in Table 2.1, there are differences between the previous research and studies compared to the current research. The previous studies used only one method mentioned in the study to build the predictive maintenance in specific studies. However, the current research will make use of the four methods of Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) in the creation of predictive maintenance in terms of the Batik printing machine. The first method, predictive maintenance, will be the basis for the whole research, serving as an answer to the formulated problem. The second method, LSTM, will allow for long-term dependency handling, but is computationally heavier and slower due to the number of parameters. The third method will provide a simpler architecture and faster training, but it may struggle with very long sequences. By having LSTM and GRU combined into a hybrid method, it will take both of their advantages while also covering their issues, such as by

having GRU handles short dependencies while LSTM handles long-term memory, or by having a model train with GRU at first, then tune it with LSTM for better memory capture. Lastly, the optimization method will use the results from previous methods to find the optimum threshold for the predictive maintenance at which the maintenance should be proactively performed.

CHAPTER III
RESEARCH METHODOLOGY

3.1 Research Subject

The subject of the current research is a garment manufacturing company that delves into the industry of making Batik clothing which is intending to rely on machine data to manage their maintenance processes. The research will then provide insights into the effectiveness of integrating prediction maintenance model results in the company decision making capability.

3.2 Research Object

The object of the research that is being observed is the Batik printing machine designed to produce Batik in large quantities. This includes historical machine usage, especially data concerning things that are related to machine breakdown and maintenance. The research aims to assess how effectively a predictive maintenance model can provide actionable insights from machine conditions.

3.3 Data Collection

To comprehensively understand predictive maintenance, the data collection process for this research involves gathering primary and secondary data. The former, primary data is data that is collected based on someone's hands-on experience or from direct data collection such as field observations, surveys, and interviews. As for the latter, secondary data is the accessible data based on previous studies or research that are related to the current topic of the thesis.

Primarily, the data that has been collected is based on the reports readily available from the Batik manufacturing company. The data consists of things required to conduct a maintenance process, enabling the use of methodology such as preventive maintenance, corrective maintenance, and predictive maintenance. Some of the data are including but not limited to temperature data, load usage, days since last maintenance, and machine operating hours.

Secondly, the data is based on recollection of assumptions or theories from previous studies that are treading on the same or similar topic as the current thesis. The recollections are then used to build both the literature review and theoretical basis of the study. By comparing the recollections with one another, it will be easier to come up with new assumptions or hypotheses that can then be answered thoroughly in the study.

3.4 Research Instruments

The research instruments used for data collection are:

1. Sensor devices

These instruments are responsible for the collection of machine conditions such as temperature, operating hours, and other relevant data required to be monitored to provide data for the machine breakdown likelihood.

2. Machine learning algorithms

The primary tools and target of the research that is being built and tested are the RUL prediction model and the optimization of the safe buffer. It resulted in the combination of the previous instruments, where various sensor data and historical RUL data are combined to finally be modeled into a machine learning algorithm.

3.5 Maintenance Cost Optimization Model

Using data collected from the Batik printing machine, the first objective in data processing is to predict the Remaining Useful Life (RUL) of the machine. While accurate RUL predictions are good, they are not enough to guide optimal decision-making on their own since maintenance activities need to be done not too early and not too late. This is where a cost-based optimization plays a crucial role in determining the optimal safe buffer, which is defined as the number of remaining operating hours before failure at which predictive maintenance should be proactively triggered.

The safe buffer in this case serves as a threshold where, if the predicted RUL is equal to or less than this buffer, a predictive maintenance action is performed. If it is greater, maintenance is suspended, assuming that corrective actions are likely to be performed during the suspended period. The model has the purpose of balancing predictive maintenance cost and corrective maintenance cost, where corrective maintenance is significantly more expensive due to unplanned downtime and the potential for high equipment damage.

Based on that, the following mathematical model will be used for optimizing the cost-based maintenance actions:

$$TotalCost(B) = C_p \cdot \sum_{i=1}^{n} 1_{PdM}^{B}(i) + C_C \cdot \sum_{i=1}^{n} (1 - 1_{PdM}^{B}(i)) \tag{3.1}$$

Where:

- B : Safe buffer threshold (hours)
- *TotalCost(B)* : Total cost at said threshold (Rupiah)
- C_p : Cost of predictive maintenance (Rp 305.000)
- C_c : Cost of corrective maintenance (Rp 655.000)
- n : Total number of maintenance checks
- $1_{PdM}^{B}(i)$: 1 if $RULi \leq B$, else 0 (indicator function)
- $RULi$: Predicted RUL for check i

The mathematical model above states that for every check i, if the predicted RUL is less than or equal to buffer B, predictive maintenance is triggered at cost C_p. Otherwise, no maintenance is done, and a failure is assumed to occur later, hence incurring cost C_c. The objective is to find the buffer value that minimizes the total cost.

The optimization for the safe buffer is performed by iterating over a range of possible buffer values, with an example of 1 to 70 hours, which is the range of RUL found within the predicted data, and computing the total cost for each. The buffer B that results in the minimum total cost is chosen as the optimal safe buffer following this formula:

$$B^* = \min_{B \epsilon [1, RUL_{max}]} TotalCost(B) \tag{3.2}$$

This cost optimization model is then applied to the RUL predictions obtained from the LSTM-GRU hybrid neural network model. The result of this optimization will provide a practical threshold for maintenance teams within the company to follow when scheduling maintenance interventions based on the machine's actual condition predictions.

3.6 Research Flow

The following figure 3.1 illustrates the flow of the research considering the use of LSTM and GRU models to build the prediction maintenance system and the optimization of safe buffer via Jupyter Notebook:

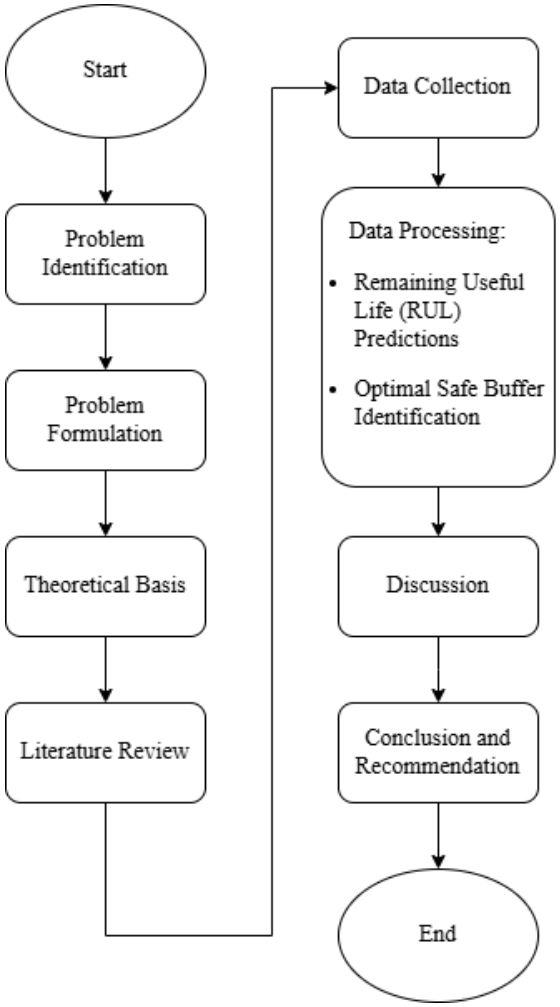


Figure 3.1 *Research Flow*

The explanation for each step in the research flow is as follows:

1. Problem Identification

   In this part of the research, the subject of the research was observed to be identified as where the problem lies. The problem can be identified by finding gaps between the current situation of the Batik printing machine conditions and the current maintenance strategy.

2. Problem Formulation

   After the problem was identified, a problem formulation was then done to understand how the problem occurred. At the same time, the research objective was also set in this phase as an answer to the formulated problem, wherein this research, the goal was to build a prediction model for Batik printing machine's RUL and the optimization model to find the safe buffer.

3. Theoretical Basis

As the research objective has been set, theories relevant to the study were then compiled in this part to serve as a basis for the assumption that comes with the research. The theories were found by using several keywords in relation to the study, such as predictive maintenance, neural networks, LSTM, and GRU models.

4. Literature Review

   Previous research and studies related to the current research were also reviewed to compare which parts have not been discussed, so that it can be used as a gap in research where the current research may act as an answer for the identified gap.

5. Data Collection

   When all the foundations of the research were established, data were then collected in the form of primary and secondary data. The primary data came from the Batik embroidery company, specifically the Batik printing machine data, which was the subject of the research, while the secondary data was compiled from various previous research and studies.

6. Data processing

   As the main objective, the development of a prediction model for RUL and the optimization of a safe buffer were done by using Jupyter Notebook along with previously gathered data. There are two main parts done during this section, including:

   - Remaining Useful Life (RUL) predictions

     In developing models for the predictive maintenance system of the Batik printing machine, the first step was to predict RUL using historical data in the form of time series data. The prediction of RUL will utilize LSTM and GRU models of neural networks to obtain data that is similar to the actual data and can serve as a representation of the whole dataset. The resulting prediction of RUL can then be used in further data processing to optimize the maintenance process.

   - Optimal safe buffer identification

     After the RUL predictions were obtained, the next step is to find the optimal safe buffer that can act as a threshold on when the machine should proactively go to maintenance before the end of RUL happens. To find the optimal safe buffer, a range of values of safe buffer is going to be simulated in the prediction model, whereas the best value of safe buffer that offers the lowest costs will be chosen as the result. The optimal safe buffer can then be used in the application of maintenance strategies for the Batik printing machine.

7. Results and Discussion

In the event of maintenance strategy completion, the results were then discussed to see the predicted RUL and optimal safe buffer effectiveness in improving maintenance strategy efficiency and in reducing the total costs required for the whole maintenance process. Challenges that occurred throughout the research may also be mentioned as a reminder or precaution for future research.

8. Conclusion and Recommendations

   At last, conclusions were provided based on the research findings in the form of a key takeaways summary. Recommendations were also given in order to encourage further actions or improvements for a similar project in the future.

CHAPTER IV
DATA COLLECTION AND DATA PROCESSING

4.1 Company Profile

PT. X in Pekalongan, Central Java, is a company dawdling in fabric manufacturing, specifically Batik fabrics. As for Batik itself, it is among the most popular types of fabrics in Indonesia. To meet the demand of Batik locally and overseas, the company specializes in manufacturing a large quantity of Batik sheets using specially designed machinery.



Figure 4.1 *Batik fabric products*

Manufacturing on a high scale with machinery that works continuously for hundreds of hours, even with some breaks in between, will have some impact on the machines in the long term. PT X. themselves used Batik printing machines in the production of Batik sheets. The machine is a specialized machine designed to automate the process of applying Batik designs onto fabric. Using machinery for the mass production of Batik fabrics brings about several advantages, such as reducing production and labor time, where in traditional Batik making, a sheet of Batik may need tens of days to finish, maintaining consistent quality, and supporting high amounts of demand.



Figure 4.2 *High-end Batik printing machine*

(Source: Batik Industrial Group)

Relying on Batik printing machines, Batik designs can be done digitally at first using related CAD software. The fabric that has been pre-treated, cleaned, and stretched will then be applied with the selected pattern using the machine. The finished product can then undergo some treatment to fix its colors and enhance its durability. During the entire process, sensors are used to monitor certain parts of the machine, such as its nozzle and tip, in order to sense the temperature and load usage of the machine, which can be used to calculate the machine's remaining useful life. Using data collected from the sensors and conducting data analysis, a predictive maintenance system can then be built in order to keep the machine in good health and increase its lifespan.

4.2 Data Collection

From the sensors established in the machine, data from 100 production cycles were obtained. The following table shows collected machine data.

Table 4.1 *Batik printing machine data*

No.	Temperature (C)	Load Usage (Units)	Last Maintenance (Days)	Operating Hours (Hours)
1	69,09	601	41	296
2	62,89	580	42	360
3	76,31	525	41	344
4	94,61	407	40	304
5	68,73	552	38	280
6	64,20	355	42	328
7	52,65	448	39	312
…	…	…	…	…
100	55,46	395	35	320

Based on the table above, it can be seen that there are several different kinds of data obtained from the machine. Later in the study, these four types of data will be used as the feature during data processing. The four types of data themselves can be explained as follows:

1. Temperature (C)

   The first data from the sensors is the machine temperature data. It shows the average temperature of the machine during the entire process of Batik production in one cycle. The data appears to be calculated in Celsius (C).

2. Load usage (Units)

   The second data from the machine is the load usage. It shows the number of units produced within one cycle. The data appears to be calculated in units.

3. Last maintenance (Days)

   The third data from the machine is the last maintenance data. It shows how long it has been since the last time the machine got maintenance. The data appears to be calculated in days.

4. Operating hours (Hours)

   The fourth dataset of the machine is the operating hours data. It shows the amount of time spent producing Batik fabrics in one production cycle. The data appears to be calculated in hours.

Using the data above, several new datasets can be obtained using certain calculations. The following table shows the results of the calculations.

Table 4.2 *Extended Batik printing machine data*

No.	RUL (Hours)	Data Sampling	Down time day
1	48	78	84
2	54	129	136
3	43	179	184
4	24	224	227
5	52	265	272
6	60	314	322
7	69	361	370
…	…	…	…
100	62	4792	4800

Based on the table above, it can be seen that there are several different kinds of data obtained from further calculations using the previous dataset. Later in the study, one of the datasets, which is the remaining useful life (RUL) data, will be used as the target during data processing. The three types of data themselves can be explained as follows:

1. Remaining useful life (RUL)

The first data from the calculations is the remaining useful life data. It was calculated by using multiple regression on the previous four data. It shows the amount of time the machine is expected to continue operating before failure occurs or requires critical maintenance. The data appears to be calculated in days, as in how many days the machine has left.

2. Data sampling

   The second data point from the calculations is the data sampling. It shows the sequential time marker when data collection of the machine condition was conducted, meaning that the number is not a unit of time and will increase as more data is collected.

3. Down time day

   The third data point from the calculations is the downtime day data. It shows the estimation of when the machine is expected to go down as in failure or stop operating. Similar to data sampling, the number shown is a sequence that will grow larger with more data.

The next collection of data is the maintenance cost data, which is divided into three big parts depending on the maintenance method, including preventive, corrective, and predictive maintenance. Each type of maintenance has different kinds of cost components, ultimately leading to a different amount of total cost. The cost components for each type of maintenance and their total cost can be seen in the following table.

Table 4.3 *Costs of maintenance strategies*

Preventive Maintenance		**Predictive Maintenance**		**Corrective Maintenance**	
Action	**Cost**	**Action**	**Cost**	**Action**	**Cost**
Lubrication	Rp 50.000	Lubrication	Rp 50.000	Component Inspection	Rp 80.000
Cleaning	Rp 75.000	Cleaning	Rp 75.000	Minor Repair	Rp 25.000
Component Inspection	Rp 80.000	Component Inspection	Rp 80.000	Medium Parts Replacement	Rp 150.000
Minor Repair	Rp 25.000	Small Parts Replacement	Rp 100.000	Major Overhaul	Rp 200.000
				Emergency Breakdown Repair	Rp 200.000
Total	**Rp 230.000**	**Total**	**Rp 305.000**	**Total**	**Rp 655.000**

4.3 Data Processing

The data processing was done using Jupyter Notebook to create a predictive maintenance model by utilizing the collected data. The steps by which the data was processed can be considered as follows:

4.3.1 Predicting RUL

The first step in the data processing is to use the dataset containing the temperature, load usage, and the actual remaining useful life data to obtain predictions about the future remaining useful life that can be used as the basis for predictive maintenance for the company. The predictive maintenance model will utilize recurrent neural networks (RNNs), specifically long short-term memory (LSTM) and gated recurrent unit (GRU), that are used as a hybrid to build the predictive model. The step of predicting remaining useful life is as follows.

1. Importing libraries for Jupyter notebook

   There are several libraries that need to be imported into Jupyter notebooks before the data can be processed. These libraries are responsible for data handling, modeling, visualization, and tuning. To import the libraries, the following codes were used.

```
import pandas as pd
import numpy as np
import tensorflow as tf
from tensorflow.keras.models import Sequential, Model
from tensorflow.keras.layers import Dense, LSTM, GRU, Input, Dropout
from keras_tuner.tuners import RandomSearch
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
import networkx as nx
import matplotlib.pyplot as plt
```

Figure 4.3 *Python codes for importing required libraries*

   From the figure above, it can be seen that there are several libraries that are imported for data processing, with each of them serving different purposes as follows.

   - Data handling : pandas, numpy
   - Deep learning (LSTM + GRU) : tensorflow, keras
   - Data preprocessing and splitting : sklearn
   - Automates hyperparameter tuning : keras_turner
   - Visualize network architecture : networkx, matplotlib

2. Loading and preprocessing data

```
df = pd.read_excel("Batik_RUL_Updated_Data.xlsx")
print(df)
```

```
    Temperature (C)  Load Usage (Units)  Last Maintenance (Days)  \
0             69.09                 601                       41
1             62.89                 580                       42
2             76.31                 525                       41
3             94.61                 407                       40
4             68.73                 552                       38
..              ...                 ...                      ...
95            85.38                 624                       39
96            63.90                 362                       42
97            71.25                 404                       41
98            77.12                 347                       40
99            55.46                 395                       35

    Operating Hours (Hours)  RUL (Hours)  Data Sampling  Down time day  \
0                       296           48             78             84
1                       360           54            129            136
2                       344           43            179            184
3                       304           24            224            227
4                       280           52            265            272
..                      ...          ...            ...            ...
95                      328           34           4604           4608
96                      344           62           4651           4659
97                      320           47           4700           4706
98                      328           41           4747           4752
99                      320           62           4792           4800
```

Figure 4.4 *Dataset loading and result*

After the libraries are imported, the required dataset also needs to be prepared and then loaded into the notebook before beginning to be preprocessed. The figure above shows the Python code to load the data (The dataset is required to be in the same folder as the notebook file) and the loaded dataset.

```
scaler = MinMaxScaler()
features = ["Temperature (C)", "Load Usage (Units)", "Last Maintenance (Days)", "Operating Hours (Hours)"]
target = "RUL (Hours)"

X = df[features]
y = df[target]

X_scaled = scaler.fit_transform(X)
y_scaled = scaler.fit_transform(y.values.reshape(-1, 1))

X_train, X_test, y_train, y_test = train_test_split(X_scaled, y_scaled, test_size=0.2, random_state=42)
```

```
X_train = X_train.reshape((X_train.shape[0], 1, X_train.shape[1]))
X_test = X_test.reshape((X_test.shape[0], 1, X_test.shape[1]))
```

Figure 4.5 *Python codes for preprocessing*

The next step is to do data preprocessing, preparing the dataset to make it suitable for predictive model building using LSTM and GRU later during the processing. Based on the figure above, the preprocessing can be divided into two steps, starting with the first set of code responsible for the selection of features (Temperature, load usage, last maintenance, and operating hours) and target (RUL), then scaling them to normalize the data of both

features and target. After scaling, the dataset was then split 80% into training (X_train, y_train) and 20% into testing (X_test, y_test). The second set of codes is responsible for reshaping the dataset into a 3D input shape required for LSTM and GRU, since their layers in Keras expect the input to be in the form of samples, time steps, and features. Reshaping is required for LSTM and GRU to work properly during the data processing.

3. Defining the building model and tuning the hyperparameter

With the data being preprocessed, the next step, which is to build the model, is done by relying on the Keras Tuner library. The neural network model combined both LSTM and GRU as layers to learn from sequential data, which in this case is for predicting remaining useful life (RUL). Here, LSTM is responsible for capturing time-based dependencies while GRU is responsible for refining the learned patterns. In addition to both layers, the library also combines a dropout rate to prevent overfitting and a learning rate to control the model stability for learning. Lastly, the best model obtained is returned for further testing and evaluation. The following figure is the Python code to build the model.

```
def build_model(hp):
    model = Sequential()
    model.add(LSTM(hp.Int('lstm_units', min_value=32, max_value=128, step=32), return_sequences=True, input_s
    model.add(GRU(hp.Int('gru_units', min_value=32, max_value=128, step=32)))
    model.add(Dropout(hp.Float('dropout', min_value=0.2, max_value=0.5, step=0.1)))
    model.add(Dense(1, activation='linear'))
    model.compile(optimizer=tf.keras.optimizers.Adam(hp.Choice('learning_rate', values=[1e-2, 1e-3, 1e-4])),
                  loss='mse',
                  metrics=['mae'])
    return model
```

Figure 4.6 *Python codes for building a model*

After the model is built, there is a need to find the best hyperparameters for the neural network model. This step was done by relying on the RandomSearch function in Keras Tuner library, where multiple trials are run with different combinations and then trained to find out the best combination, which has the lowest validation loss. For this study, the trials are done a total of 10 times with each trial getting trained twice to reduce randomness. Each model within the trial is tested for 50 epochs and has 20% of its training data used as validation to evaluate validation loss. The best hyperparameters are then stored for further use in building and training the final model.

```
tuner = RandomSearch(
    build_model,
    objective='val_loss',
    max_trials=10,
    executions_per_trial=2,
    directory='hyperparameter_tuning',
    project_name='hybrid_lstm_gru'
)

tuner.search(X_train, y_train, epochs=50, validation_split=0.2, verbose=1)
best_hps = tuner.get_best_hyperparameters(num_trials=1)[0]
```

```
Trial 10 Complete [00h 00m 31s]
val_loss: 0.07818057388067245

Best val_loss So Far: 0.0016250658081844445
Total elapsed time: 00h 04m 59s
```

Figure 4.7 *Python codes for hyperparameter testing and results*

4. Training the best model and evaluation

When the best model and its hyperparameters have been obtained, the next step is to train said model and evaluate its performance over time as the final model. In this study, the best model is trained for a total of 100 epochs with 20% of the training data for validation. The following figure is the Python codes for training the best model.

```
best_model = tuner.hypermodel.build(best_hps)
history = best_model.fit(X_train, y_train, epochs=100, validation_split=0.2, verbose=1)
```

```
Epoch 5/100
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 107ms/step - loss: 0.0770 - mae: 0.2359 - val_loss: 0.0158 - val_mae: 0.0975
Epoch 6/100
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 86ms/step - loss: 0.0463 - mae: 0.1831 - val_loss: 0.0289 - val_mae: 0.1555
Epoch 7/100
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 105ms/step - loss: 0.0388 - mae: 0.1573 - val_loss: 0.0388 - val_mae: 0.1772
Epoch 8/100
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 93ms/step - loss: 0.0328 - mae: 0.1442 - val_loss: 0.0118 - val_mae: 0.0820
Epoch 9/100
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 103ms/step - loss: 0.0172 - mae: 0.1130 - val_loss: 0.0250 - val_mae: 0.1305
Epoch 10/100
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 99ms/step - loss: 0.0227 - mae: 0.1318 - val_loss: 0.0153 - val_mae: 0.0982
Epoch 11/100
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 85ms/step - loss: 0.0122 - mae: 0.0889 - val_loss: 0.0223 - val_mae: 0.1208
Epoch 12/100
```

Figure 4.8 *Python codes for training the best model and results*

The next step after the training is evaluation. The final model is evaluated on the test data to find out about the test loss or mean square error (MSE) and test mean absolute error (MAE), both of which indicate the accuracy of the model to predict the remaining useful life (RUL) for data it has never seen before. Following the figure below, it can be seen that the value of the test MSE is equal to 0.00346 which can be interpreted as good as it shows a very low average square error while the value of the test MAE is equal to 0.05006 which can be interpreted as good as it shows about 5% error of the scaled range which is from 0 to 1.

```
loss, mae = best_model.evaluate(X_test, y_test, verbose=0)
print(f"Test Loss: {loss}, Test MAE: {mae}")
```

```
Test Loss: 0.003462802618741989, Test MAE: 0.050060998648405075
```

Figure 4.9 *Python codes for evaluating the best model and results*

5. Predicting remaining useful life and plotting

   Having the final trained model means that RUL values can now be predicted for the test dataset. There are basically two steps starting with predicting RUL values using the model with scaled output, then converting the scaled values back to original units, which in this case is in hours. After that, the plotting library, Matplotlib, is imported to visualize the prediction, whereas some sklearn functions are imported to measure average prediction error and to measure how well the predicted values approximate the actual values. It can be seen from the figure below that the value of root mean square error (RMSE) is equal to 3.0600, which is good since the lower it is, the better, showing that the predictions are closer to the actual values. As for the R-squared result, it shows the value of 0.9531, which can be considered excellent since the model fits the data very well, explaining most of the variation in the target values.

```
y_pred = best_model.predict(X_test)
y_test_unscaled = scaler.inverse_transform(y_test)
y_pred_unscaled = scaler.inverse_transform(y_pred)
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 472ms/step
```

```
import matplotlib.pyplot as plt
from sklearn.metrics import mean_squared_error, r2_score
```

```
rmse = np.sqrt(mean_squared_error(y_test_unscaled, y_pred_unscaled))
print(f"RMSE: {rmse:.4f}")
```

```
RMSE: 3.0600
```

```
r2 = r2_score(y_test_unscaled, y_pred_unscaled)
print(f"R-squared: {r2:.4f}")
```

```
R-squared: 0.9531
```

Figure 4.10 A *set of Python codes for predicting RUL and evaluation*

6. Visualizing network architecture

   After obtaining and verifying the results of predicted RUL, the neural network architecture showing how the predicted RUL is obtained can be visualized using Matplotlib and NetworkX libraries. The architecture basically consists of three parts, which are the input

features (Temperatures, load usage, last maintenance day, and operating hours), the hidden layers (LSTM and GRU), and the output target (RUL). The following figure shows the lines of code responsible for visualization, starting with labelling nodes for each neuron, connecting neurons edge one another to show the network structure, and giving different colors for each neuron to distinguish the layers.

```
def plot_neural_network_custom(input_neurons, hidden_layers, output_neurons):
    """
    Plots a neural network with labeled neurons and customized layer colors.
    """
# Initialize graph
    G = nx.DiGraph()
    pos = {}
    layer_gap = 2
    neuron_gap = 1

# Input Layer
    for i, name in enumerate(input_neurons):
        G.add_node(f"Input {i+1}", layer="Input", label=name)
        pos[f"Input {i+1}"] = (0, -i * neuron_gap)

# Hidden Layers
    prev_layer = [f"Input {i+1}" for i in range(len(input_neurons))]
    layer_x = layer_gap
    for l_idx, num_neurons in enumerate(hidden_layers):
        curr_layer = [f"Hidden{l_idx+1} Neuron {i+1}" for i in range(num_neurons)]
        for j, neuron in enumerate(curr_layer):
            G.add_node(neuron, layer=f"Hidden {l_idx+1}", label=f"H{l_idx+1} N{j+1}")
            pos[neuron] = (layer_x, -j * neuron_gap)
        for p_node in prev_layer:
            for c_node in curr_layer:
                G.add_edge(p_node, c_node)
        prev_layer = curr_layer
        layer_x += layer_gap

# Output Layer
    output_layer = [f"Output {i+1}" for i in range(len(output_neurons))]
    for i, name in enumerate(output_layer):
        G.add_node(name, layer="Output", label=output_neurons[i])
        pos[name] = (layer_x, -i * neuron_gap)
    for p_node in prev_layer:
        for o_node in output_layer:
            G.add_edge(p_node, o_node)

# Draw graph
    plt.figure(figsize=(12, 8))
    nx.draw(
        G, pos,
        with_labels=True,
        labels=nx.get_node_attributes(G, 'label'),
        node_size=5000,
        node_color=[
            'skyblue' if G.nodes[node]['layer'] == "Input" else
            'lightgreen' if "Hidden" in G.nodes[node]['layer'] else
            'salmon'
            for node in G.nodes
        ],
        font_size=10,
        font_color='black',
        edge_color='gray',
        arrowstyle='-|>',
        arrowsize=15,
        connectionstyle='arc3,rad=0.1'
    )
    plt.title("Neural Network Architecture", fontsize=16)
```

Figure 4.11 *Python codes for visualization design*

With the visualization design done and run, the neural network architecture can then be visualized. The figure below shows the lines of code required for visualizing and the results of the visualization. It can be seen that in the input layers there are 4 features, 96 LSTM and GRU units in the hidden layers based on the best models, and one target in the output layers.

```
input_features = features
hidden_layers_neurons = [best_hps.get('lstm_units'), best_hps.get('gru_units')]
output_labels = [target]

plot_neural_network_custom(input_features, hidden_layers_neurons, output_labels)
```

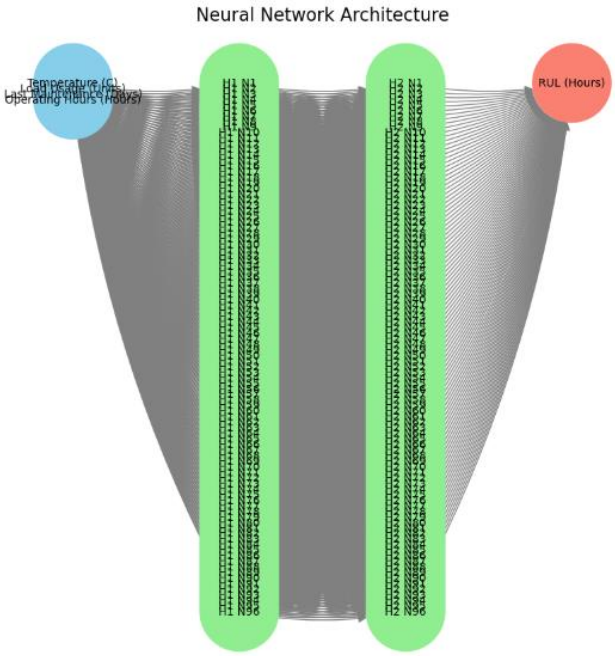


Figure 4.12 *Python codes for visualizing neural network architecture and results*

7. Displaying training and testing data for transparency

   After all is done, the last step should be transparency of the data, which can be done by displaying both training and testing data in the form of 2D format. The former, training data, is displayed in tabular view with each row representing a training sample, while each column to a feature, while the final column corresponds to the RUL target for said sample.

```
train_data = pd.DataFrame(X_train.reshape(X_train.shape[0], -1), columns=[f"Feature_{i+1}" for i in range(X_train.shape[2])])
train_data['Target (RUL)'] = y_train
print("Training Data:")
print(train_data)
```

```
Training Data:
    Feature_1  Feature_2  Feature_3  Feature_4  Target (RUL)
0    0.339498   0.486486        0.8        0.0      0.634615
1    0.384932   0.831081        0.4        0.0      0.673077
2    0.454110   0.493243        0.3        0.3      0.480769
3    0.080365   0.121622        0.9        0.6      0.942308
4    0.159817   0.854730        0.9        0.4      0.692308
..        ...        ...        ...        ...           ...
75   0.993379   0.158784        0.8        0.0      0.115385
76   0.840868   0.479730        0.3        0.3      0.192308
77   0.815753   0.692568        0.5        0.4      0.211538
78   0.402283   0.668919        0.4        0.9      0.615385
79   0.391096   0.216216        0.6        0.8      0.538462

[80 rows x 5 columns]
```

Figure 4.13 *Python codes for displaying training data and results*

Lastly, for the testing data, it is also displayed in tabular view showing a comparison between the test input features, the actual RUL, and the model's predicted RUL for each test sample.

```
test_data = pd.DataFrame(X_test.reshape(X_test.shape[0], -1), columns=[f"Feature_{i+1}" for i in range(X_test.shape[2])])
test_data['Actual RUL'] = y_test_unscaled
test_data['Predicted RUL'] = y_pred_unscaled
print("\nTesting Data with Predicted RUL:")
print(test_data)
```

```
Testing Data with Predicted RUL:
    Feature_1  Feature_2  Feature_3  Feature_4  Actual RUL  Predicted RUL
0    0.044977   0.597973        1.0        0.8        72.0      66.506630
1    0.212329   0.969595        0.6        0.9        61.0      57.017731
2    0.926941   0.905405        0.0        0.5        24.0      26.086180
3    0.763014   0.385135        0.7        0.4        37.0      33.833450
4    0.307078   0.834459        0.9        0.9        54.0      52.779285
5    0.378539   0.864865        0.2        0.1        49.0      52.867279
6    0.091781   0.283784        0.7        0.5        63.0      65.949303
7    0.729909   0.827703        0.4        0.2        32.0      35.576538
8    0.798174   0.895270        0.0        0.6        29.0      31.549532
9    0.405251   0.922297        0.6        0.2        48.0      50.411652
10   0.445890   0.101351        1.0        0.2        46.0      49.861626
11   0.606164   0.956081        0.0        0.9        38.0      38.927547
12   0.945205   0.354730        0.7        0.9        22.0      24.259701
13   0.387671   0.094595        0.1        0.9        53.0      51.354057
14   0.518265   0.121622        0.6        0.2        47.0      46.779541
15   0.397032   0.756757        0.3        0.0        52.0      52.337658
16   0.220091   0.516892        0.6        0.5        58.0      59.243797
17   0.097717   0.550676        0.9        1.0        60.0      63.669792
18   0.319178   0.668919        0.1        0.9        59.0      52.866051
19   0.978082   0.895270        0.3        0.1        25.0      24.540415
```

Figure 4.14 *Python codes for displaying testing data and results*

4.3.2 Finding the best safe buffer with minimum cost

After the predicted RULs have been obtained using the testing and training data, the next big step is to find the best or optimal threshold for maintenance optimization with the purpose of determining the best time to do maintenance, also known as a safe buffer, with the lowest cost. This was done using the previously established mathematical model in the previous chapter by applying the model to the predicted RUL results.

First of all, it is determined that the decision variable is the safe buffer B, expressed in hours. To calculate this variable, two maintenance cost parameters were required as the following table:

Table 4.4 *Maintenance cost parameters*

Symbol	Description	Value
C_p	Cost of one predictive maintenance action	Rp 305.000
C_c	Cost of one corrective maintenance action	Rp 305.000

Preventive maintenance action is not included in this action because the goal is to find the most economical trade-off between predictive and corrective for the given RUL sequence. Preventive maintenance action will still be applied later on the maintenance checks with RUL higher than the optimal safe buffer.

For each inspection i (i = 1, …, n = 20), an indicator variable as follows,

$$1_{PdM}^{B}(i) = \begin{cases} 1 \; if \; RUL_i \leq B \\ 0 \; otherwise \end{cases}$$

is introduced, where RUL_i is predicted RUL obtained previously using Jupyter Notebook. Then, using previously introduced mathematical model in the previous chapter it can be seen below.

$$TotalCost(B) = C_p \cdot \sum_{i=1}^{n} 1_{PdM}^{B}(i) + C_C \cdot \sum_{i=1}^{n} (1 - 1_{PdM}^{B}(i)) \tag{4.1}$$

with further application of the maintenance cost parameters, the total maintenance cost associated with candidate buffer *B* is therefore,

$$TotalCost(B) = 305000 \cdot \#PdM + 655000 \cdot \#CM \tag{4.2}$$

where:

- #PdM : Number of inspections for which $RUL_i \leq B$
- #CM : Number of inspections for which $RUL_i > B$

The equation (4.2) is then tested by performing a full-enumeration search for integer buffer values,

$$B \in [1,70] \; hours,$$

where 70 exceeds the maximum predicted RUL (66.51 hours) and therefore captures the entire feasible range.

The following table shows the summary of the resulting cost profile from the predicted RUL, tested using the given formula.

Table 4.5 *Summary of resulted cost profile*

Safe Buffer *B* (hours)	**#PdM**	**#CM**	**Total Cost**
24	3	17	Rp 12.040.000
30	5	15	Rp 11.000.000
40	7	13	Rp 9.960.000
50	10	10	Rp 9.600.000
60	15	5	Rp 8.275.000
67	20	0	Rp 6.100.000

It is obtained as a result that the optimal safe buffer with minimum total cost is when the safe buffer is at 67-hours RUL, which means that for every predicted RUL with lower than 67 hours remaining, predictive maintenance will be conducted, which in this case, for the 20 predicted RUL, the total cost is Rp 6.100.000. This result can then be applied to the actual 100-maintenance checks data of the Batik printing machine.

CHAPTER V
DISCUSSION

5.1 Maintenance Optimization Overview

The maintenance of industrial equipment is a core aspect in an industry that directly impacts production in its reliability, since proper maintenance will help minimize unexpected breakdowns and control the costs of production. In this study, the machine analyzed for its performance is the Batik printing machine. By leveraging the performance data of the machine over time, optimization models with the purpose of identifying the best maintenance timing with the lowest cost were developed using the help of Jupyter Notebook.

In recognition of traditional maintenance strategies such as corrective maintenance and scheduled preventive maintenance where the former has issues in terms of cost, generally bloated due to the reason that the maintenance is done after the machine is having a breakdown, and the latter which has issues in terms of wasteful maintenance where the machinery does not need to be maintained based on its current health, this study utilizes predictive maintenance principles. The reason for choosing predictive maintenance is to make the maintenance scheduling more dynamic, where it directly depends on the current state of the machine using a data-driven approach.

The prediction model based on Remaining Useful Life (RUL) was developed in this study using previously collected data of the Batik printing machine, which comes in the form of a time series data. With the data providing the machine condition and operational history, the remaining hours before the machine is likely to have a breakdown are reflected in the predicted RUL. Having predicted the RUL, the actual degradation of machines can then be responded to more closely in the maintenance decisions, reducing the likelihood of previous problems such as overflowing costs and wasteful maintenance.

One final concept introduced in the study to optimize the maintenance of the Batik printing machine is the safe buffer. Before RUL reaches zero, there is a need for an existence that represents a critical threshold at which a proactive action of maintenance should be

performed, and this is the role of a safe buffer. In determining the safe buffer, two previous critical concerns of minimizing overflowing costs due to unexpected breakdown and avoiding early and wasteful maintenance need to be balanced. Then, with the resulting optimal safe buffer, the maintenance will ensure reliability without waste.

5.2 Predicted RUL Analysis

One central objective in this study involved developing and analyzing predicted RUL data for the Batik printing machine. Using a hybrid model with the combination of Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) layers, the predicted RUL was generated. Both of the layers, deep learning architectures, were used since they are suitable for sequential data such as the sensor readings of the Batik printing machine, capturing both long-term and short-term dependencies.

From the historical data amounting to 100 RULs and each of the conditions in the time series, 80 were taken as the training set, while the other 20 were taken as the test set. By training the 80 historical data points, the model algorithm learned how to predict the remaining lifespan of the machine based on its current and past conditions. Then, with the application of the model algorithm to the test set, 20 new RUL predictions were obtained, which provide a dynamic, time-based figure of the machine's health.

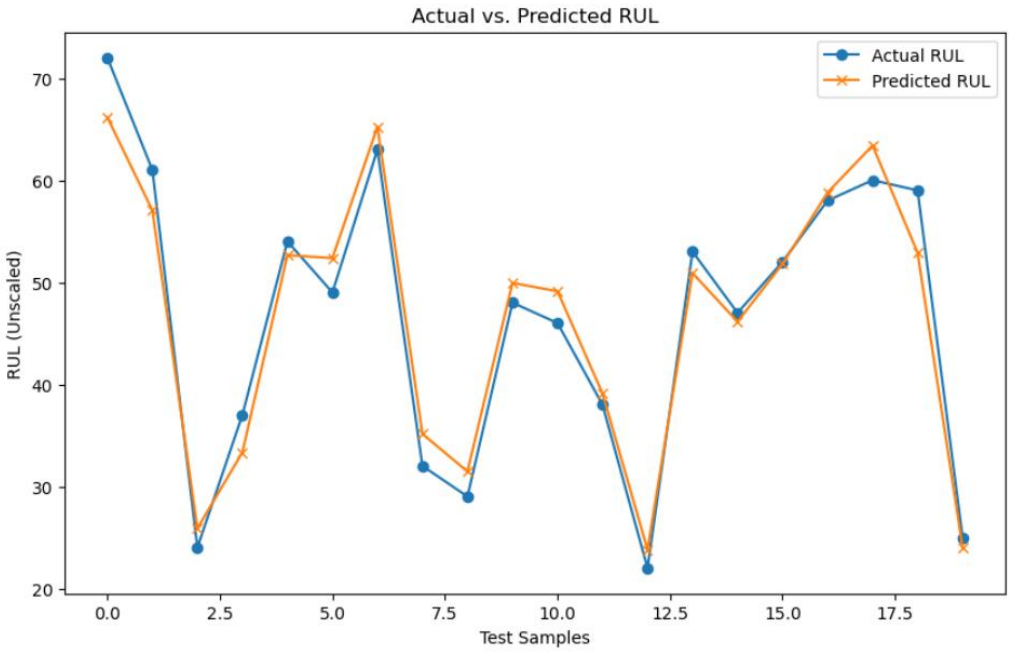


Figure 5.1 *Actual versus predicted RUL*

It can clearly be seen in the figure above that the predicted RUL closely resembles the actual test RUL, meaning that the predicted RUL can represent the actual RUL of the Batik

printing machine; hence, it can be used for further data analysis. The predicted RUL results were also validated by calculating the root mean square error (RMSE) and the R-squared value. It was obtained that the value of RMSE is equal to 3.0600 while the value of R-squared is 0.9531. The former, showing a low value, means that the predicted RUL is factually closer to the actual value, while the latter can be interpreted as the model fits with the data, showing only ~5% of error.

5.3 Optimal Safe Buffer Analysis

As mentioned previously, the safe buffer represents the exact hour when proactive maintenance should be carried out before the end of the machine's RUL to prevent unexpected breakdown. Determining the optimal safe buffer was one of the main concerns in this study, especially for the maintenance optimization process. By establishing the safe buffer threshold, it can directly affect the maintenance process, specifically in terms of maintenance frequency and controlling the cost of maintenance activities.

The safe buffer threshold was calculated by utilizing a mathematical model that was developed previously, along with the obtained data of predicted RUL. To find the optimal safe buffer that offers minimal maintenance cost, the mathematical model was tested together with the 20 predicted maintenance checks using several scenarios in which each scenario has different safe buffer thresholds from 1 to 70 hours, where predictive and corrective maintenance become the cost parameters for the testing. It followed a simple structure where if the RUL at a maintenance check was less than or equal to the selected safe buffer, predictive maintenance was performed while if the RUL was higher than the selected safe buffer, no maintenance action was taken, and it is assumed that corrective action will occur later. With this approach, each safe buffer was evaluated for its practical effect on maintenance timing.

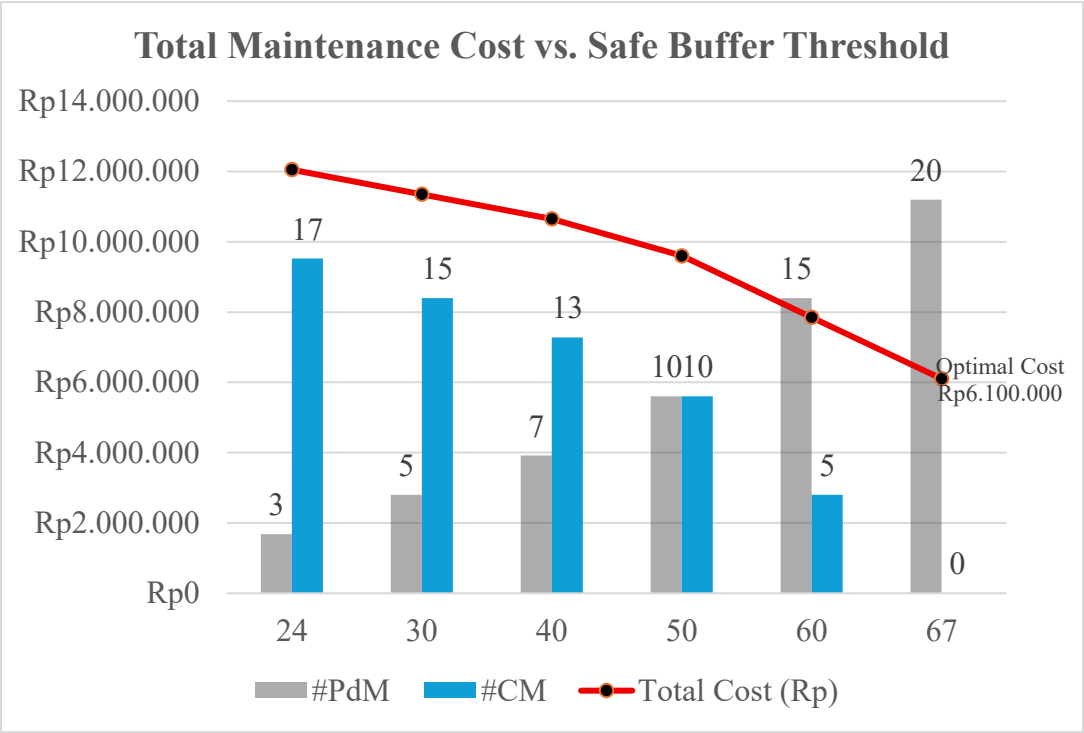


Figure 5.2 *Optimal safe buffer threshold and its total cost*

The figure above shows the result of the optimal safe buffer calculation. It demonstrated that the optimal safe buffer serves as a trade-off point between predictive and corrective maintenance that offers the lowest cost for maintenance. Since the cost of corrective maintenance action is too high, it is preferred that it be reduced, and instead, predictive maintenance is performed since it has a significantly lower cost. It can be seen in the figure that with the safe buffer being higher and higher, more predictive actions are performed, and fewer corrective actions are needed. At a certain point, it is found that no corrective maintenance action is needed, and predictive maintenance is enough. This point is when RUL is exactly at 67 hours. This RUL threshold represents a predictive maintenance strategy that is most cost-effective, and risk-balanced specifically for Batik printing machines' actual condition as captured by the RUL predictions.

5.4 Application of Results to Full Operating Hours

With the RUL done and predicted, and the optimal safe buffer determined, it is then necessary to apply these findings to the actual dataset of the Batik printing machine's operation lifecycle. This is done to prove that the safe buffer strategy is not merely a theoretical solution for a small test set but can also be used in the actual practice of maintenance planning. The first thing to be applied is the result of the optimal safe buffer, which is at 67-hour RUL. The application for this is simply done by finding which of the 100-maintenance checks have less than or equal to

67 hours RUL. If the RUL is indeed found to be said value, the maintenance action to be taken is predictive maintenance. The following table shows the application of a safe buffer to the actual RUL of the Batik printing machine in 100 time series data.

Table 5.1 *Optimal safe buffer application to the actual RUL*

RUL Range (Hours)	Frequency	Maintenance Strategy(s)	Cost (Rp)	Total Cost (Rp)
≤ 67	90	Predictive Maintenance	Rp 305.000	Rp 27.450.000

In the table above, it is found that from the total of 100 maintenance checks and their actual RULs, there are 90 checks whose RULs are less than or equal to 67 hours. This means that all 90 checks can be maintained using a predictive maintenance method over the 4,800-day operation. As a result, the total maintenance cost for the predictive maintenance conducted on the 90 checks is Rp 27.450.000. However, there are 10 maintenance checks that have RUL higher than 67 hours, which means that predictive maintenance could not be performed on these checks. To solve this, the remaining 10 checks are then grouped to find the total remaining operation days of the Batik printing machine, as in the actual data. The following table is the grouped remaining maintenance checks.

Table 5.2 *Grouped remaining maintenance checks*

Last Maintenance (Days)	Operating Hours (Hours)	RUL (Hours)	Data Sampling	Down Time Day
39	312	69	78	87
35	304	69	125	134
38	288	69	172	181
39	280	71	220	229
40	312	72	269	278
45	320	70	323	332
44	328	69	376	385
41	296	69	426	435
37	296	69	472	481
45	344	72	526	535

From the table above, it can be seen that the remaining unmaintained checks have a total of 535 days of operation. Using this data and applying the company's strategy to perform preventive maintenance every 30 days, it is obtained that the total preventive maintenance strategy is around 18 times over the remaining 535 days. Combined with the cost of preventive maintenance being Rp 230.000 for each maintenance action, the total cost of maintenance is obtained at Rp 4.140.000. Overall, in the 4800 days of Batik printing machine operation, these

preventive maintenance actions may be performed in the gap that exists between predictive maintenance that was calculated before.

Concluding both preventive and predictive maintenance strategies obtained in the research, the proposed solution offers a Batik printing machine maintenance strategy that is more dynamic with the combination of two maintenance strategies that also has lower frequency of maintenance at 108 times total over 4800-days of operation, reducing the number of unnecessary downtime and lowering the total cost of maintenance at Rp 31.590.000.

In comparison, the previous strategy adopted by PT. X is entirely a preventive maintenance strategy. For the 4800-day operation of the Batik printing machine, the company adopted preventive maintenance which was conducted every 30 days of production. In total, the number of maintenances conducted using preventive strategies is 160 times in frequency, making the total cost for maintenance amount to Rp. 36.800.000. The exact comparison between the previously adopted strategy by the company and the proposed solution from the study can be found in the following table.

Table 5.3 *Comparison of previous strategies and the proposed solution*

Comparative Aspect	**Original Strategy**	**Proposed Solution**
Maintenance Strategy(s)	Preventive	Preventive and Predictive
Maintenance Frequency	160 Preventive	90 Predictive 18 Preventive
Total Maintenance Frequency	160 times	108 times
Total Cost of Maintenance	Rp 36.800.000	Rp 31.590.000

From the table above, it appears that the proposed solution with the application of several maintenance strategies using the 67-hour RUL of optimal safe buffer as the basis for determining which strategy should be applied depending on the current value of machine's RUL, has been proven to be better than the original strategy in terms of time and cost as the maintenance done in the proposed solution are not as often for the whole case of 4800-day operation. This ultimately leads to the proposed solution having significantly lower total cost for maintenance compared to the original strategy, with the difference between the two of Rp 5.210.000. This whole difference in maintenance frequency and total cost of maintenance

clearly shows that the proposed solution serves as a better strategy to be adopted by PT. X for the Batik printing machine operation, specifically for its maintenance.

In the end, it is also important to note that no corrective actions are seen in the result of the Batik printing machine. This can be seen as a good thing since, in common maintenance practice, one of the goals is to minimize corrective maintenance, as it incurs the highest cost compared to other maintenance strategies by causing unplanned downtime and may result in production losses. The fact that corrective maintenance did not appear in the result serves as evidence of the predictive strategy's effectiveness. However, this is still limited to the simulation results, whereas real-world environments are inherently more unpredictable. Some failures may still occur due to external factors such as operator error, electrical issues, or an undetected sensor fault in which case, corrective actions may still be needed.

Finally, using the previous example of application, the optimal safe buffer can then be used for future maintenance planning of the Batik printing machine. By then, it will be easier to see which maintenance strategy should be adopted and how much the maintenance costs overall. Thus, the integrated maintenance strategy may achieve a balance of reliability and cost efficiency while also be more dynamic as the proposed solution relies on the actual machine conditions instead of a rigid scheduled maintenance.

5.5 Interpretation and Limitations

Overall, this study highlights the potential of data-driven maintenance planning, especially by leveraging the application of RUL predictions and optimal safe buffer. At the central point of the study, the actual machine conditions become the concern aimed to be aligned more effectively with the maintenance decisions. As a result, predictive maintenance is then ensured to be carried out just before the failure risk becomes significant.

The implications of the approach within the study are closely related to industrial maintenance strategies as they provide a clearer roadmap for maintenance planning and resource allocation. The reason for these implications is that the approach changes the focus of maintenance from scheduled preventive maintenance or corrective maintenance to a more adaptive framework that responds to real-time equipment health dynamically. With the integration of the results into an existing preventive maintenance schedule, maintenance teams or planners can achieve a reliable and balanced maintenance strategy.

Unfortunately, there are still a few important limitations within the study to consider. First, the calculation of RUL prediction and optimal safe buffer is done on the 20 testing sets

from the full 100 time series data, assuming that these samples represent the entire operational period. Second, the costs for maintenance strategies used in the study are static, which may not be true and vary in real-world applications, as there are several uncertainties, such as labor availability, supply issues, and equipment-related challenges. Third, the model does not consider potential variations that could influence the actual RUL, such as operator errors and environmental conditions.

For future research, these limitations could be addressed by considering the incorporation of dynamic cost structures, larger datasets, and real-time data for ever-changing RUL updates. Despite these limitations, the study offers an optimized maintenance timing, bridging the gap between preventive, corrective, and predictive maintenance strategies.

CHAPTER VI
CONCLUSION AND RECOMMENDATION

6.1 Conclusion

Based on the study that had been done in regard to Batik printing machine of PT. X in Pekalongan, starting from literature study, data collection, and processing, and up until discussion, some conclusions of the study can be seen as follows:

1. Predictive maintenance that utilizes LSTM and GRU models was used in the study in order to predict RUL of the Batik printing machine to then find the optimal safe buffer by analyzing the predictions and simulating different safe buffer values, serving as a balance between cost control and intervention during the maintenance process. It was obtained that the optimal period where predictive maintenance should be conducted is when the RUL reaches the 67-hour mark. At this point, predictive maintenance served its purpose to avoid excessive or costly maintenance that frequently occurred in other maintenance strategies.
2. Predictive maintenance developed using LSTM and GRU models was confirmed in this study to be able to enhance overall maintenance efficiency and reduce the total cost for the Batik printing machine. Reliable estimates of the machine's Remaining Useful Life were provided using the developed RUL prediction model, giving a way of understanding the machine's degradation process more thoroughly, which can help in improving overall efficiency and is used to find the optimal safe buffer. From the application of the final result into the historical data of Batik printing machine, it was observed that in the proposed solution, the number of maintenance frequencies was 108 times in total along with the cost of Rp 31.590.000 while in the original strategy, the number of maintenance frequencies was 160 times which brings the total cost to Rp 36.800.000. This proves that by using the proactive approach of the proposed solution, the overall maintenance costs are able to be reduced compared to solely relying on preventive maintenance in the original strategy. Furthermore, the proposed solution ensures that maintenance resources are only used when truly necessary, hence improving the efficiency of the company's maintenance strategy. All

in all, this proposed solution was able to achieve a balanced, data-driven maintenance strategy for the Batik printing machine.

6.2 Suggestion

Based on the process throughout the study and its results, several suggestions can be considered for related future research, such as:

1. Future researchers should consider incorporating larger and more diverse datasets that include different machine states and operational scenarios for expanding the RUL prediction model in order to improve the applicability of the predictions over a wider range of conditions.
2. Future researchers should consider assimilating dynamic cost structures for the maintenance costs that may vary due to internal and external factors, which should enhance the developed model's realism and applicability in real industrial environments.
3. Given the results for the Batik printing machine, future researchers could test a similar predictive maintenance optimization framework on other types of industrial equipment, which should enable the generalization of the approach and identify whether, in different manufacturing contexts, similar reliability improvements and cost savings can be achieved.
4. For the company itself, it is recommended to integrate the predictive maintenance strategy developed in this research, specifically the use of optimal safe buffer obtained from RUL predictions, into their actual maintenance planning system. The department that should be responsible for this implementation and act as a leader is the Industrial Engineering (IE) department, which is responsible for production efficiency and process monitoring. A collaboration with the maintenance department may also be conducted to schedule maintenance activities based on real-time or regularly updated RUL predictions.

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APPENDIX

Collected Batik Printing Machine Data

No	Temperature (C)	Load Usage (Units)	Last Maintenance (Days)	Operating Hours (Hours)	RUL (Hours)	Data Sampling	Down time day
1	69,09	601	41	296	48	78	84
2	62,89	580	42	360	54	129	136
3	76,31	525	41	344	43	179	184
4	94,61	407	40	304	24	224	227
5	68,73	552	38	280	52	265	272
6	64,20	355	42	328	60	314	322
7	52,65	448	39	312	69	361	370
8	73,22	487	44	320	46	414	420
9	91,60	498	42	336	27	462	465
10	54,08	462	35	304	69	503	512
11	86,30	593	35	328	29	553	557
12	59,36	459	35	320	65	597	605
13	65,32	526	36	352	59	649	656
14	83,56	401	41	296	34	697	701
15	87,07	533	40	312	31	741	745
16	51,34	549	38	288	69	783	792
17	72,68	423	42	360	49	837	843
18	54,52	543	39	280	71	882	891
19	70,87	358	45	296	46	936	942
20	95,14	427	45	296	23	987	990
21	68,49	619	44	288	48	1034	1040
22	74,12	505	40	280	43	1080	1085
23	55,36	412	42	320	63	1127	1135
24	77,57	496	44	360	38	1180	1185
25	64,90	542	41	360	57	1230	1237
26	91,01	388	36	288	30	1273	1277
27	71,23	474	38	304	45	1315	1321
28	62,59	455	43	352	56	1365	1372
29	75,17	431	37	328	47	1413	1419
30	85,64	567	44	320	34	1463	1467
31	77,89	611	35	352	38	1511	1516
32	94,18	593	38	288	25	1554	1557
33	52,16	441	40	312	72	1597	1606
34	68,32	356	36	352	53	1650	1657
35	87,42	433	43	288	33	1700	1704
36	86,34	328	44	288	35	1748	1752
37	94,98	462	41	360	20	1797	1800
38	74,73	512	41	352	39	1844	1849
39	51,61	510	45	320	70	1894	1903
40	67,92	584	37	288	49	1940	1946
41	60,63	574	39	320	62	1986	1994
42	63,90	584	42	280	59	2036	2043
43	54,86	364	44	328	69	2087	2096
44	61,64	425	36	312	56	2135	2142
45	64,79	575	44	352	54	2186	2193
46	84,76	442	42	312	37	2235	2240
47	52,24	441	37	344	65	2283	2291
48	88,12	457	35	312	31	2330	2334
49	91,28	389	39	360	25	2379	2382
50	67,76	351	38	304	50	2420	2426

Collected Batik Printing Machine Data (Continued)

No	Temperature (C)	Load Usage (Units)	Last Maintenance (Days)	Operating Hours (Hours)	RUL (Hours)	Data Sampling	Down time day
51	71,18	467	35	360	46	2471	2477
52	68,47	392	41	344	48	2520	2526
53	83,22	491	35	352	38	2570	2575
54	60,64	615	41	352	61	2619	2627
55	73,19	623	41	344	45	2670	2676
56	66,21	472	43	280	53	2719	2726
57	90,16	449	40	320	29	2766	2770
58	68,12	471	39	344	54	2813	2820
59	67,73	391	43	296	51	2863	2869
60	54,45	620	35	360	61	2914	2922
61	94,85	375	43	280	26	2965	2968
62	52,70	592	41	296	69	3009	3018
63	87,61	550	42	288	28	3060	3064
64	62,29	568	39	336	60	3106	3114
65	54,07	337	37	296	69	3151	3160
66	93,60	622	36	288	25	3196	3199
67	67,60	561	36	328	54	3240	3247
68	74,00	588	41	336	41	3289	3294
69	61,82	358	42	336	57	3336	3343
70	58,34	581	44	312	56	3387	3394
71	91,94	596	35	320	24	3434	3437
72	88,17	470	38	304	30	3475	3479
73	73,66	404	35	312	46	3518	3524
74	92,74	433	42	352	22	3568	3571
75	75,62	410	37	280	49	3608	3614
76	74,33	372	43	296	44	3657	3663
77	60,98	481	41	320	58	3704	3711
78	55,62	491	44	360	60	3756	3764
79	80,35	526	38	320	38	3804	3809
80	92,24	563	37	328	23	3850	3853
81	83,31	573	39	296	32	3892	3896
82	68,07	499	37	320	56	3936	3943
83	84,00	358	41	336	36	3985	3990
84	53,31	505	45	344	72	4035	4044
85	78,74	406	37	320	44	4084	4090
86	76,39	397	37	296	48	4127	4133
87	59,60	464	40	312	59	4173	4180
88	75,44	339	43	304	48	4223	4229
89	68,20	574	39	280	55	4268	4275
90	91,06	463	40	344	27	4318	4321
91	74,04	364	41	296	47	4362	4368
92	89,24	518	43	288	31	4411	4415
93	68,96	526	39	352	52	4459	4466
94	83,84	575	44	320	32	4510	4514
95	66,28	430	41	344	50	4557	4563
96	85,38	624	39	328	34	4604	4608
97	63,90	362	42	344	62	4651	4659
98	71,25	404	41	320	47	4700	4706
99	77,12	347	40	328	41	4747	4752
100	55,46	395	35	320	62	4792	4800