UNLOCKING OPERATIONAL EFFICIENCY THROUGH RELIABLE ASSET DATA: A CASE STUDY OF MAINTENANCE STRATEGIES IN COMPANY X

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Preface

In this document, I am pleased to be presenting my thesis, which marks the culmination of my bachelors degree at the University of Twente. This journey has been a great source of academic and personal growth. I aim to provide readers with an in-depth overview of my research's findings and insights.

Throughout my bachelor's degree in Industrial Engineering and Management, I've been on a challenging yet rewarding route, not just academically but also personally. I am really excited to deliver my thesis, which is a reflection of my commitment to my studies and the effort I put forward.

I want to start off by sincerely thanking both my primary supervisor, Mahak Sharma, and my secondary supervisor, Ipek Topan. Their constant feedback, trust, and support have greatly influenced the successful progression and quality of this thesis.I truly thank you for your time and effort.

I also must express my sincere gratitude to my company supervisor, whose welcoming attitude and support have aided me to use my research in a real-world setting. The knowledge and insights gained from working with him have expanded my industry perspective and experience significantly.

I must conclude with an important acknowledgement towards my family and friends for offering continuous support in this endeavor.

I extend my gratitude to everyone who has played a role, big or small, in this academic journey. I hope that the knowledge and insights contained within these pages contribute to the broader understanding of the subject matter and inspire further research in this field.

Ahmed Elsawaf
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Management Summary

This thesis delves into the critical aspect of asset data quality within Company X, a global manufacturing organization facing challenges in maintaining accurate and reliable asset information. The main focus of this research is to address the problem of poor data quality, particularly in asset criticality classification, and its impact on maintenance operations and decision-making, which led us to the formulation of the research question: How can Company X attain a sufficient baseline of data quality to facilitate the transition from a budget-based maintenance strategy to a data-driven one?

The first phase of the study involved an in-depth context analysis to understand how asset data is generated, used, and stored within Company X. It became evident that poor data quality, specifically mismatched asset criticality between SAP and the plant list, had adverse effects on maintenance strategies, resulting in additional costs and inefficiencies.

To resolve this issue, the research developed a methodology for data analytics to address the asset data mismatches. Using data analytics, integrating software, and physical verification, a significant a selected pilot Plant Z was selected for application of our findings. Plant Z was first operating with a 63% asset criticality match. The successful implementation of this methodology resulted in Plant Z increasing its match by 23%, becoming a well-performing plant, with 86% of assets correctly criticalized across all data sets. These results exemplify the potential of data-driven maintenance to optimize operations and resource allocation.

Furthermore, the research introduces a tool, the Incoming Asset Standardized Flowchart Tool, which acts as a standardized guide for employees when handling incoming assets. By utilizing this flowchart as a guide when dealing with new incoming assets, Company X can reduce human data entry errors, ensuring accurate asset registration and setup, ultimately improving data quality from the outset.

The research then goes to outline the significance of data governance policies. By establishing clear roles, responsibilities, and data quality standards, Company X can foster a culture of data consciousness and accountability, driving employees to actively contribute to data accuracy and consistency to maintain reliable asset data withing the organization.

The management summary concludes by emphasizing the importance of asset data to effective decision-making and proactive maintenance strategies. By empowering employees with the knowledge of data's impact on operations, Company X can foster a data-driven culture, driving continual improvement and cost savings.

In summary, this thesis offers the practical solutions of data cleansing and the standardization of processes for Company X to enhance asset data quality and aid the transition towards data-driven maintenance. After the implementation of the asset quality improvement process, an operating plant saw a significant improvement, of which the rest of the plants will soon follow. The future implementation of the Incoming Asset Standardized Flowchart Tool would then come to prevent the same issue from reoccurring in the future and provide a reliable data quality baseline for Company X to transition to a data-driven maintenance policy.

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ERP	Enterprise resource planning
SAP	Systems Applications and Products
FMCG	Fast Moving Consumer Goods
AMEA	Asia Pacific, Middle East, and Africa
LATAM	Latin America
MPSM	Managerial Problem-Solving Method
MTBF	Mean Time Between Failure
OEE	Overall Equipment Effectiveness
MTTR	Mean Time to Repair
FLOC	Functional Location
OEM	Original Equipment Manufacturer
CIL	Clean, Inspection, and Lubrication
BOM	Bill Of Materials
MRO	Maintenance Repair Operations
PMs	Preventative Maintenance Instructions
IDC	Internal Data Center

1.0 Introduction

Company X is a multinational food and beverage company that was formed in 2015, being one of the largest food and beverage companies in the world and has a diverse portfolio of well-known brands. Company X operates in more than 40 countries and offers a wide range of products including condiments, sauces, cheese, dairy products, snacks, and ready-to-eat meals.

The company is known for its iconic products such as Ketchup, Macaroni & Cheese, and others. These product brands have established themselves as household names over the years and are recognized for their quality and taste. With eight $1 billion+ brands and global sales of approximately $25 billion, Company X is a well-known and trusted, multinational company that is considered a pioneer for FMCG (Fast Moving Consumer Goods) in the food and beverage industry.

Company X operates on a global scale, with offices, production plants, and customers in all over the globe. As in any FMCG company, Company X is a very sophisticated business that includes extensive decision-making processes that encompass every small detail in their production, it is a highly sensitive industry that needs constant assessment and improvement.

Figure 1 illustrates the multinational presence of Company X, encompassing various operational zones. The management structure of the organization is decentralized, with each operating zone having its own dedicated management team exclusively responsible for the operations within that zone. However, these management zones collectively report to a central management board, fostering an environment conducive to the exchange of innovative ideas and practices across all zones. Consequently, despite their individual autonomy, the departments operate as interdependent entities by actively sharing insights, findings, and data.

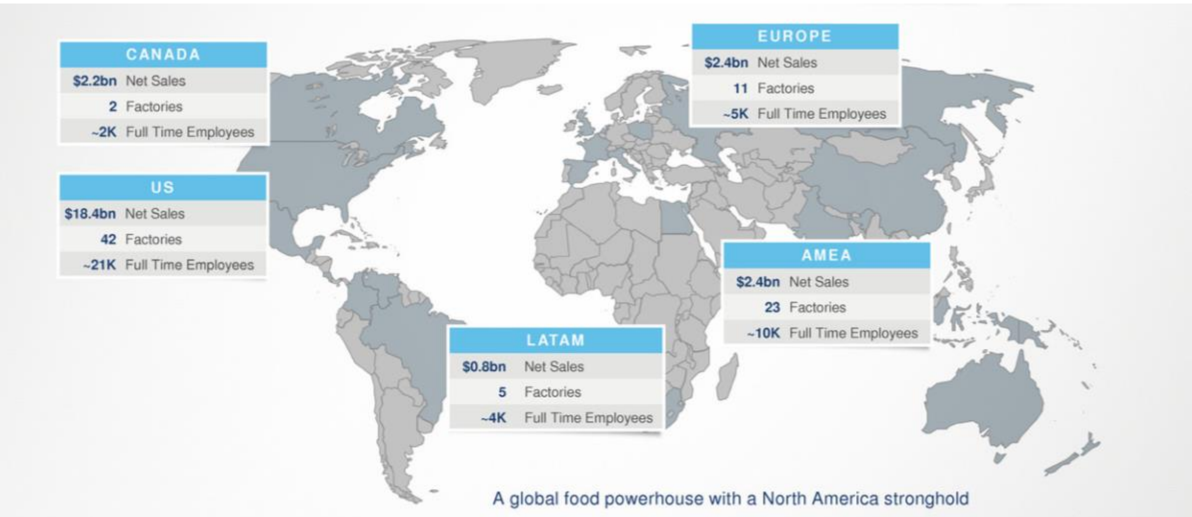


Figure 1: Company X's Operating Zones

Company X's Amsterdam branch is organized into three departments, each aligned with a specific zone delineation as follows: 1) Local Dutch Market, 2) International Zone encompassing AMEA, EUROPE, and LATAM (as depicted in Figure 1), and 3) Global Zone encompassing the United States and Canada (as depicted in Figure 1).

The scope of this research pertains to the Global department at Company X. Within this department, I am engaged in overseeing the operations of the existing 32 production plants situated in North

America. To facilitate effective management, the Global department consists of numerous sub-departments or work units, each entrusted with distinct functional responsibilities. Specifically, I am situated within the Global Manufacturing department, which assumes a comprehensive oversight role in managing all aspects of manufacturing across the North American plants. Furthermore, I am an integral part of the Global Maintenance Manufacturing team, which possesses a specialized focus on the maintenance operations associated with the production plants.

1.1 The Problem

The problem first rises when Company X had a merger with Company Y, in the aims of uniting two key players in the industry and achieving market dominance in the food and beverage industry. Even though the merger is beneficial to both parties, the transition for Company X has not been smooth, raising a few adverse effects on Company X.

During the merger process between Company X and Company Y, the organizations faced a complex task of aligning their distinct business and operational practices. Company X had long-standing traditional methods deeply ingrained in its culture, while Company Y, known for its innovative approach, operated with more agile and contemporary practices. As the two companies integrated, these differences gave rise to discrepancies in processes and procedures across various departments.

While concerted efforts were made to facilitate a smooth transition, challenges persisted, hindering some areas from reaching their full potential. In this context, the global maintenance department of Company X encountered significant hurdles, resulting in a noticeable decline in performance and overall efficiency. The impact of this situation is particularly crucial as maintenance inefficiencies can have cascading effects on asset management and overall operational effectiveness.

A deteriorating Mean Time Between Failures (MTBF) serves as a clear indicator of declining asset reliability in Company X. When MTBF decreases, it signifies that assets are experiencing failures at a higher frequency, leading to increased downtime and reduced production output. Frequent breakdowns not only disrupt manufacturing processes but also strain maintenance resources as they allocate more time and effort to repair and restore equipment.

Conversely, a rising Mean Time to Repair (MTTR) in Company X also demonstrates the maintenance team's inefficiency in addressing equipment failures. As MTTR increases, it indicates that the maintenance personnel are taking longer to rectify breakdowns, further exacerbating the impact of unscheduled downtime. Prolonged repair times hinder production schedules, diminish output, and translate into higher maintenance costs.

The maintenance department is facing an increase in their unscheduled downtime, which is driven by a combination of increasing MTBF and prolonged MTTR. The unpredictability of these equipment failures disrupts production cycles, affecting throughput, customer deliveries, and overall profitability. Moreover, recurring downtime strains the relationship with clients, leading to potential contractual penalties and reputational damage.

The declining Overall Equipment Effectiveness (OEE) in Company X represents another critical aspect of its poor maintenance performance. OEE serves as a pivotal metric that meticulously quantifies how efficiently the company's assets are utilized throughout the production process. As OEE experiences a drop, it sheds light on various inefficiencies in the equipment utilization, such as frequent downtime, prolonged changeovers, or underperformance issues. These unfavorable conditions translate into lower production yields, increased production costs per unit, and ultimately reduced overall profitability for the organization. The compounding effect of suboptimal OEE underscores the urgency to address maintenance challenges and optimize asset management to regain operational excellence and financial stability.

Moreover, poor maintenance practices may manifest as inadequate Preventive Maintenance (PM) planning and execution. Insufficient or untimely PM tasks can result in overlooked maintenance needs, leading to accelerated equipment degradation and increased risks of unexpected failures. The absence of a solid Predictive Maintenance (PdM) program further escalates the situation, as the maintenance department lacks the capability to anticipate failures and take proactive measures.

The root cause of poor maintenance department performance can be multifaceted, including issues with labor competence, insufficient maintenance training, outdated maintenance strategies, and suboptimal utilization of data and analytics. Addressing these technical aspects requires a comprehensive approach, involving skill development programs for maintenance personnel, implementation of data-driven maintenance practices, investment in predictive maintenance technologies, and the establishment of standardized maintenance procedures which would lead to smooth maintenance operations by efficient recourse allocation.

The focal point of this thesis revolves around the identification of the root cause behind the efficiency issues plaguing Company X's global maintenance department. The formulation of a problem cluster, illustrated in Figure 2 below, highlights a collection of interconnected factors that have been investigated and identified as contributing factors to the department's underperformance.

The areas to be investigated are efficiency of existing maintenance strategies in Company x, high maintenance costs of Company X, data availability, and data consistency, enabling a thorough understanding of the various factors influencing maintenance department performance. The aim of

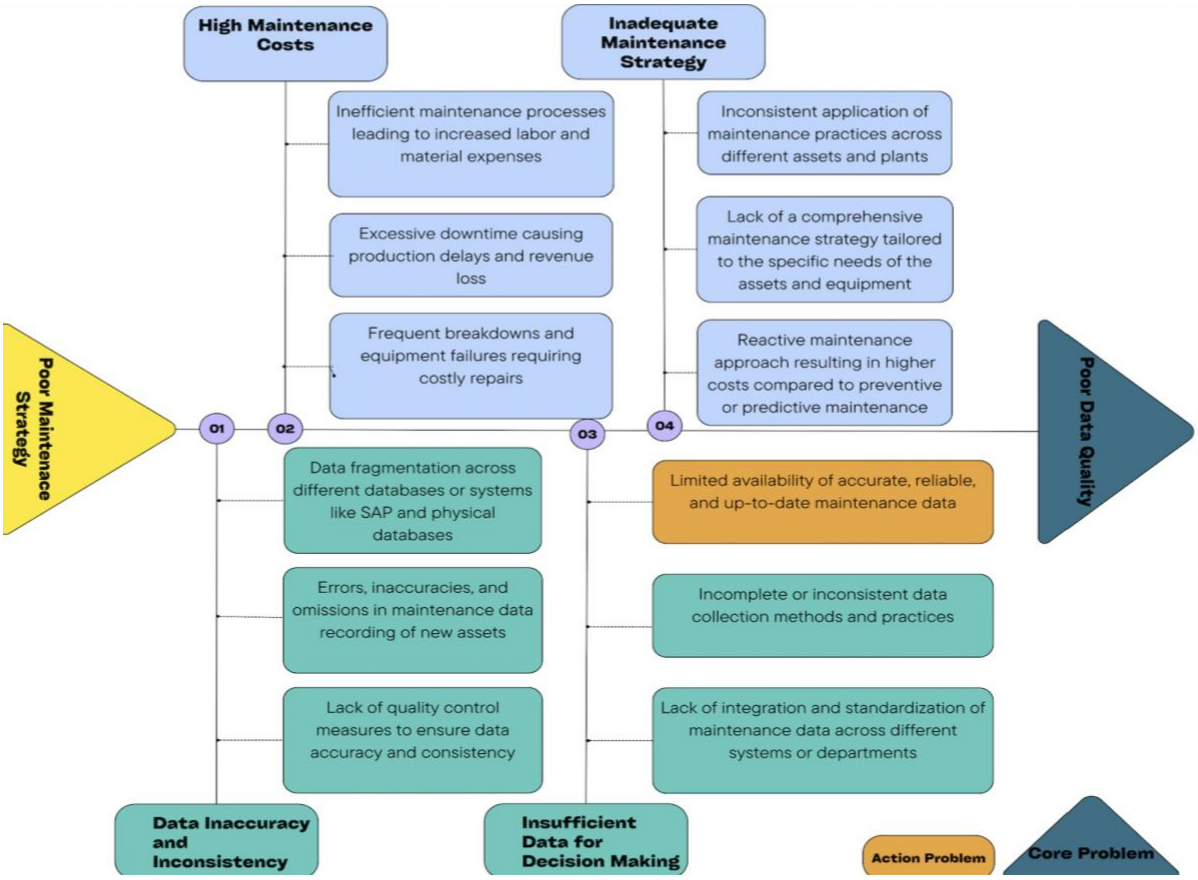


Figure 2: Problem Cluster

this cluster is to uncover the underlying core problem that lies at the core of these challenges, which would be followed be the identification of the core and action problems of this research.

1.2 Core Problem

While taking the four main dimensions into analysis in Figure 2, the core problem identified is "Poor Data Quality". This refers to the significant issue of the asset and equipment maintenance data being of such low quality and reliability to the extent that it disrupts the company's ability to make informed maintenance decisions using its current strategy.

1.2.1 Existing Assets:

What exactly does “poor data quality” refer to? In the context of this research, poor data quality refers to the misclassification of an asset’s criticality. Where many assets possess different criticalities in SAP versus their actual criticality. Asset criticality is the level of importance assigned to assets in a manufacturing company based on their potential impact on operations and business performance. It involves categorizing assets and prioritizing resources, investments, and maintenance activities accordingly. Higher criticality assets require more attention and preventive maintenance to minimize downtime and disruptions, ensuring optimal production efficiency and customer satisfaction. Company X uses an interactive excel tool with four factors (safety, environment, quality, production) to determine asset criticality, assessing severity and probability to calculate an overall criticality score (A-E). Each factor has different levels of severity on a scale from "Not Likely" to "Nearly Certain."

As reliable data serves as the foundation for all and especially effective decision-making , having un-reliable data does not just obstruct the company from implementing any changes to its maintenance strategy since achieving reliable data is the baseline for strategy assessment, but more importantly adds unnecessary costs to Company x. The formulation of Figure 3 below easily explains the importance of asset data quality to Company X and what effects poor data quality portrays on Company X’s performance.

Figure 3: Cause and Effect Loop : Poor Equipment Data Quality

The figure showcases a negative cause and effect loop Company X experiences as a result of exhibiting poor asset data quality. The loop is listed in an orderly manner in the following:

1. **Poor Equipment Data Quality:** The loop begins with the presence of "Poor Equipment Data Quality." This refers specifically to the misclassification of asset criticality, where assets have different criticality levels in SAP compared to their actual criticality.
2. **Incorrect Asset Criticality Assignment in SAP:** As a consequence of poor data quality, the company may incorrectly assign an asset with a criticality level of "A" (highly critical) in the SAP system, instead of its actual criticality level of "C" (mid-critical).
3. **Automated Processes and Unnecessary Costs:** The incorrect assignment triggers automated processes within SAP, leading to significant additional costs for the company. SAP's automated systems, based on the erroneously assigned criticality, initiate unnecessary procurement of extra spare parts and unnecessary maintenance activities.

4. **Financial Implications and Inefficiencies:** The misclassification results in financial implications, as the company incurs expenses associated with acquiring surplus inventory and conducting unnecessary maintenance work. These additional costs could have been avoided if the asset had been assigned its correct criticality level.
5. **Diverted Resources and Operational Impact:** The financial implications of poor equipment data quality create inefficiencies within the company's operations. Valuable resources, including time, manpower, and financial resources, are diverted towards addressing the consequences of the misclassification, taking away from other productive areas within the organization.
6. **Overall Organizational Performance:** The diversion of resources and operational impact may ultimately affect the overall organizational performance. The company may experience reduced productivity, increased downtime, and potential delays in production schedules, leading to customer dissatisfaction and reputational risks.
7. **Impact on Maintenance Performance:** The loop comes full circle as the poor maintenance performance is a direct result of the initial poor equipment data quality. The misclassification of asset criticality in SAP leads to unnecessary costs, inefficiencies, and diverted resources, all of which collectively contribute to poor maintenance performance.

1.2.2 Incoming Assets

The problem at Company X arises from the absence of a standardized system or process flow for handling asset data when new assets are introduced. This lack of standardization leads to human errors, inconsistencies, and subpar data quality for the assets. According to the International Organization for Standardization (ISO), a standardized system refers to "the set of interrelated or interacting elements that establish policies and objectives, and the processes and procedures to achieve those objectives." In this context, a structured system for asset data handling would consist of established policies, procedures, and processes guiding employees on how to accurately and consistently enter and record data for new assets.

At Company X, a significant challenge arises due to the poor quality of existing asset data and the way new assets are handled when they arrive. The core issue is the lack of a standardized system or process flow to govern how employees should deal with the data related to these assets. As a result, each employee might have their own approach to entering and recording asset data, leading to inconsistencies and errors.

When new assets are introduced into Company X's inventory, a critical moment arrives when the asset data needs to be accurately entered and recorded. This stage is essential as it forms the basis for effective asset management throughout their entire lifecycle. However, the absence of clear guidelines and procedures means that employees rely on their individual knowledge and experience to handle this process, resulting in varying data quality and integrity.

Due to the lack of a structured system, asset criticalities might be misclassified, causing skewed assessments of asset importance and improper resource allocation. Such inconsistencies not only affect maintenance operations but also permeate through the entire organizational decision-making process. This lack of standardization can lead to inefficient resource usage and less informed strategic choices.

Additionally, without a standardized process flow, employees may unintentionally overlook or neglect important data fields, leaving them incomplete or inaccurate. The omission of essential data fields can hinder effective asset tracking, limit the ability to conduct meaningful analyses, and impede the implementation of predictive maintenance strategies. As a consequence, the overall reliability and usability of asset information are diminished, making it harder for the organization to make informed decisions about asset management and optimization.

Furthermore, the lack of a standardized system contributes to data redundancy and duplications, resulting in inefficient data storage and management. Inconsistent data entry practices may also lead to data conflicts, where different data sources contradict one another, causing confusion and undermining data credibility. As a consequence, vital asset-related decisions may be made based on incomplete or conflicting data, further escalating the problem of poor data quality.

The absence of a well-defined process for handling new asset data opens the door to further complications and inefficiencies within the maintenance department. Inaccurate data can lead to ineffective maintenance planning, underestimation of asset risks, and untimely maintenance interventions. The consequences of these deficiencies ripple through the entire maintenance ecosystem, affecting equipment reliability, production schedules, and ultimately, the overall organizational performance.

To address these challenges, a structured system is needed. A structured system, in this context, refers to a set of established policies, procedures, and processes that guide employees through the entire asset data handling process in a consistent and standardized manner. This system ensures that each asset's data is entered accurately and completely, allowing for improved data quality and integrity. It also enables better asset tracking, informed decision-making, and the implementation of proactive maintenance strategies.

By implementing a structured system for data handling, Company X can overcome the data quality issues and benefit from more reliable and usable asset information. Maintenance plant managers can deal with assets in a reliable manner, resulting in smooth and complete data variables added to the system. This, in turn, will lead to more efficient maintenance operations, better resource allocation, and improved overall performance for the organization. The number of maintenance activities assigned to an asset would decrease, as well as the number of ordered spare parts, as when the system realizes poor data quality, the system would order more than the required level in order to be on the safe side of operations.

1.3 Scope

The scope of this research encompasses the asset data management practices within Company X. The department investigated in this research contains 32 production plants in its operating zone. However, the scope of this research is aimed at Plant Z. Plant Z will act as the pilot plant of this research, where the results of this research would be applied to Plant Z, and hence act as a guideline for the rest of the plants in the zone. The research is limited to the context of Company X and does not extend to other companies or industries.

1.4 Norm Vs Reality and Action Problem

The action problem identified in the problem cluster would be the limited availability of accurate, reliable, and up-to-date maintenance data and would be formally stated at the end of this section after identifying norm and reality.

In order to identify the norm and reality, there must exist a measurable variable that would be the gap that needs to be filled to transfer a stakeholder from the reality to the norm.

Criteria	# In SAP	# In Plant Criticality
A		
B		
C		
D		
E		
Total ABC	Confidential	
Total DE		
No Criticality (=#N/A)		
% of Assetts with no Criticality in SAP		
Total # of mismatches		
Total # of Assets		
% of Mismatched Assets		

Figure 4: Asset Data Variables

Figure 4 showcases the data that would be extracted and used for the selected Plant Z, it is a comparison of the same data sets for two sources to mainly measure: **% Matched Criticalities**, which refers to the percentage of total assets that share a matching criticality in SAP versus the Plant list data. It will be the primary measure of success (norm versus reality).

To obtain this metric, a comprehensive data analysis approach has been conducted and can be viewed in detail in section 4.2.1. The data analysis process aims to compare the criticality assigned to each asset in SAP with the plant's physical asset list. The goal is to confirm if there is a significant mismatch between the criticality values in the two datasets.

The analysis follows a structured framework:

1. **Data Cleansing:** Assets present in both SAP and the Plant List are identified, and any assets lacking corresponding entries in both datasets are excluded. This ensures a reliable and consistent dataset.
2. **Merging Data:** The compatible asset list from both datasets is merged to create a unified view. This facilitates easier analysis and comparison of criticality values.
3. **Extraction of Criticality Values:** Criticality values for each asset are extracted from both SAP and the Plant List datasets using Excel functions like VLOOKUP.
4. **Quantitative Assessment:** The distribution of criticality levels in each dataset is analyzed using a combination of VLOOKUP and IF functions. The percentage of mismatched assets is determined to assess the agreement between the two datasets.
5. **Summarization of Findings:** The results for the selected plant are summarized to gain an overall view.

The analysis provides valuable insights into the agreement and consistency of criticality assessments, aiding informed decision-making and improving asset management practices within the organization

Reality: Conducting the analysis for Plant Z, where the metric *% Matched Criticalities* would be conducted for the selected Plant Z, then finally averaged to gain a general measure of the situation. Where one can identify the reality of having an average of only a shocking *63% match* of asset criticalities. The **norm** for a company like Company X would be at least a 95% of asset criticality match. However, to keep the scope of this project ideal, the norm of this project, or goal, would be set to at least *75% of criticality match*. The concluding **action problem** would be the need to see an *increase of at least 12% in % Asset criticality match*.

1.5 Limitations

In this section, the potential limitations that may arise during the research will be discussed.
The first faced limitation indirectly aligns with the challenges mentioned in the data-gathering methods section. It addresses the issue of data accuracy, particularly concerning assets or equipment with varying criticality rankings between SAP (ERP software) and the production plant's asset criticality list. This discrepancy in criticality rankings creates inaccuracies and unreliable data,

leading to false purchasing quantities and additional costs. Consequently, my research faces limitations in data validity, necessitating a thorough assessment of data reliability to ensure it aligns with real-life scenarios. To address this challenge, I will implement constant monitoring and compare data from different sources to validate its accuracy and suitability for the research.

Additionally, another limitation worth considering is the availability and accessibility of certain data or documents. Some information may be classified or restricted due to company policies or confidentiality concerns. Consequently, obtaining comprehensive and unrestricted access to all relevant data may be challenging. To mitigate this limitation, I have worked closely with Company X's data administrators and stakeholders to navigate any potential data restrictions and ensure I have access to the data necessary for my research.

Furthermore, the size and scope of the research may impact the generalizability of the findings. The study focuses on Company X's specific operations and practices, which may not directly apply to other organizations in different industries or settings. While the research aims to address the specific issues faced by Company X, the findings may have limited applicability to broader contexts. However, by conducting a thorough analysis and clearly delineating the context of the study, I will strive to offer valuable insights that can inform best practices in asset data management and maintenance strategies.

In conclusion, while my research seeks to address crucial aspects of asset data quality and maintenance practices, I acknowledge potential limitations in communication, data validity of assets due to improper data collection, data accessibility, and generalizability. Through rigorous data validation, open communication with stakeholders, and a clear delineation of the research context, I aim to mitigate these limitations and provide valuable contributions to the field of asset management and data-driven maintenance strategies. The findings of these limitations are crucial to keep in mind while conducting the rest of the research. Keeping those limitations in mind, one can make error informed decisions and would naturally keep an eye out for irregularities during the research.

1.6 Validity and Reliability

Validity and reliability are important factors to consider when assessing the quality of data. Validity refers to how well the data accurately measures or represents the intended concept or phenomenon. In simpler terms, valid data gives an honest and truthful representation of what it aims to measure. For example, in a satisfaction survey for a product, valid data would ensure that the survey questions effectively capture satisfaction and that respondents provide genuine and accurate responses. Various factors can threaten validity, such as biased questions, small sample sizes, or measurement errors. Maintaining validity requires careful study design, appropriate measurement tools, and rigorous data collection methods.

Reliability, on the other hand, focuses on the consistency and stability of data over time or under different conditions. Reliable data produces consistent results when the same measurements are repeated in similar circumstances. For instance, a reliable scale consistently provides accurate weight measurements, establishing trustworthiness. Similarly, a survey that consistently elicits similar responses from the same individuals on different occasions demonstrates reliability. Random errors, inconsistencies in data collection procedures, or fluctuations in measurement conditions can undermine reliability. Researchers enhance reliability by employing standardized protocols, conducting multiple measurements, and training data collectors to minimize errors.

Both validity and reliability are crucial for obtaining meaningful and trustworthy results. Validity ensures that data accurately reflects the intended concepts, while reliability ensures consistent and dependable measurements. Researchers strive to maximize both validity and reliability to enhance the credibility and utility of their data.

1. **Validating Used Data:** To validate the existing data used in the research, a thorough examination of its sources and origin will be conducted. It is crucial to ensure that the data comes from reputable and reliable sources, such as official records or established databases. Additionally, data cross-referencing will be employed to compare information from different sources, ensuring consistency and accuracy. Any inconsistencies or discrepancies will be carefully investigated, and efforts will be made to reconcile and validate the data against reliable reference points.
2. **Validating Generated Data:** For data generated during the research, careful attention will be given to the methodologies used to collect, measure, and analyze the information. All data collection tools, such as surveys and questionnaires, will undergo a pilot testing phase to identify and rectify any ambiguities or bias in the questions. By involving a small group of respondents and conducting pre-tests, the validity of the data collection instruments will be strengthened. Moreover, data triangulation will be employed, where multiple data collection methods will be utilized to corroborate findings, ensuring a more robust and reliable dataset.
3. **Validating Interview Questions:** Interview questions will be carefully crafted to elicit meaningful and relevant responses that align with the research objectives. To ensure validity, a panel of experts or stakeholders will review the interview questions for clarity and appropriateness. Their feedback will be incorporated to enhance the validity of the questions and the subsequent responses. Additionally, during interviews, active listening and probing techniques will be employed to clarify responses and validate the accuracy of the information provided by the interviewees.
4. **Establishing Reliability:** To establish data reliability, multiple measurements will be conducted, particularly for critical variables and key indicators. Repeating measurements will help identify and address potential errors or inconsistencies. Moreover, inter-rater reliability will be ensured during data collection, where multiple researchers or data collectors independently assess and record data to ascertain consistency and agreement in their observations. Consistent results from these independent measurements enhance the reliability of the data.
5. **Data Validation and Cross-Checking:** Throughout the research process, data validation and cross-checking will be conducted regularly. This involves verifying the accuracy of data entries, identifying outliers or anomalies, and scrutinizing the data for errors. Any discrepancies will be carefully investigated and resolved to maintain data credibility.

By employing these methods of data validation for used data, generated data, and interview responses, the research aims to ensure the validity and reliability of the collected information. Valid and reliable data will strengthen the research findings, improve data quality, and enhance the credibility of the conclusions drawn. Ultimately, the adherence to rigorous data validation methods will contribute to the overall robustness and trustworthiness of the research outcomes.

1.7 Research Aims

The aim of this research is to improve the asset data quality for Company X, which involves analyzing the current data quality, formulating and applying solutions to fix the current asset criticality mismatch to achieve a reliable asset data set for the selected pilot plant, Plant Z. The final aim of this research is to formulate a solution to prevent the issue from reoccurring in the future.

1.8 Deliverables

- Methodology of fixing current asset criticality data mismatch
- Quantified improvement of asset criticality data mismatch
- Methodology of preventing future reoccurrence of poor data quality
- Recommendations on monitoring and control of asset data quality

1.9 Research Questions

After identifying the core problem of asset data quality and the action problem of the 12% gap in asset criticality data match, one can formulate the following research question in the aims of tackling the core problem and fixing or achieving the desired goal of the action problem:

How can Company X attain a sufficient baseline of data quality to facilitate the transition from a budget-based maintenance strategy to a data-driven one?

Further, a set of sub-research questions were formulated to help answer my main research question, where questions 1a till 3a will be aimed at context analysis, gaining a better understanding of the situation. Further, questions 3b till 5 are a part of the solution generation formulation. Finally, questions 5 and 6 are to explore the benefits of the solution application.

At the beginning of the following chapter, Table 1 has been formulated. For each sub-research question, the table highlights the data collection methodology used, its MPSM phase, its intended use, and research population.

1. How is Company X's asset data made, used, and stored?

    a. What type of asset data exist?
    b. Where is it stored?
    c. How is it used?

This research question aims to investigate the processes involved in the creation, utilization, and storage of asset data within Company X. It seeks to identify the types of asset data that exist, the specific locations or databases where this data is stored, and the ways in which it is utilized within the organization. The motivation for selecting this research question lies in the importance of understanding the underlying infrastructure and practices related to asset data management. By gaining insights into these aspects, it becomes possible to identify potential areas for improvement, optimize data utilization, and enhance overall data governance, leading to more efficient asset maintenance scheduling, better resource allocation, improved predictive maintenance strategies, and ultimately, increased operational reliability and cost-effectiveness for Company X.This research question is beneficial as it will provide valuable knowledge about the existing asset data management practices within Company X, allowing for informed decision-making and the potential implementation of more efficient and effective data management strategies.

2. What are the current data quality issues faced by Company X that hinder the transition to a data-driven maintenance strategy?

    a. What specific data quality dimensions (e.g., accuracy, completeness, consistency) are lacking within Company X's current data infrastructure?
    b. What are the root causes of these data quality issues, such as data entry errors, system integration challenges, or lack of data validation processes?
    c. How do these data quality issues impact Company X's ability to make informed decisions and implement proactive maintenance strategies?

This research question seeks to explore the data quality challenges that Company X is encountering, which hinder the adoption of a data-driven maintenance strategy. It aims to identify specific dimensions of data quality, such as accuracy, completeness, and consistency, that need to be improved within the organization's data infrastructure. Furthermore, the research question investigates the root causes of these data quality issues, which may include factors like data entry errors, system integration challenges, or a lack of data validation processes. Understanding these challenges and their underlying causes is essential for Company X to make informed decisions and implement proactive maintenance strategies. By addressing these data quality issues, the organization can enhance its decision-making capabilities, optimize maintenance processes, and ultimately improve asset performance and reliability.

3.How can Company X solve their current issue of mismatched asset data across multiple data sources?

a. How can the current situation be assessed and measured?
b. What method is best to match the existing mismatched assets and update the data?
c. How can the updated asset data be assessed for reliability?

This research question focuses on addressing the problem of mismatched asset data present in various data sources within Company X. The objective is to propose a solution for reconciling and aligning the inconsistent asset data. The research question encompasses several sub-questions, including how to assess and measure the extent of the current data mismatch, determining the best method to match the existing assets and update the data, and assessing the reliability of the updated asset data. By finding effective solutions to this issue, Company X can establish accurate and consistent asset data across multiple sources, leading to improved decision-making, streamlined operations, and enhanced overall data integrity.

4.How can Company X prevent the reoccurrence of un-reliable asset data?

a. What method can be applied to prevent future incoming assets from being falsely data filled?
b. How can Company X ensure the quality and consistency of these data attributes through proper data collection methods and data management practices?

This research question aims to identify measures that Company X can implement to prevent the reoccurrence of unreliable asset data in the future. It explores the construction and application of tools or processes that can detect and prevent false data entry for new assets. The solution for question 4a, creating a standardized process flowchart for the incoming asset process, has been formulated using discussions with the selected research expert, team members, and the head of global maintenance at Company X. Formulating the solution was a natural progression, driven by the clear identification of the gap in the problem cluster presented in Section 1.1. Recognizing the need to address this gap intuitively led us to propose an clear standardized process flowchart with decision-making gateways, which effectively standardizes the entire process, offering a complex easy to follow tool for stakeholders.In chapter 6, we will first further explore this option with academic literature support. Then the solution formulation methodology of the flowchart would be discussed. Question 4b goes on to explore asset data management practices to ensure the consistency of the data in the long run.

5.How can the improvement of data quality contribute to reducing maintenance costs, minimizing equipment downtime, and optimizing resource allocation at Company X?

This research question explores the potential benefits of improving data quality within Company X in terms of reducing maintenance costs, minimizing equipment downtime, and optimizing resource allocation. By enhancing the accuracy, completeness, and consistency of data, the organization can make more informed decisions regarding maintenance activities, leading to optimized resource allocation and potentially reducing unnecessary maintenance costs. Additionally, improved data quality enables proactive maintenance practices, facilitating early detection of equipment issues and reducing unplanned downtime. Investigating this research question provides Company X with insights into the potential financial and operational benefits of data quality improvement, motivating the organization to prioritize data management initiatives.

6.How can the improvement of data quality contribute to the transition from budget-based maintenance to data-driven maintenance?

This research question focuses on understanding how enhancing data quality can facilitate the transition from a traditional budget-based maintenance approach to a more data-driven maintenance strategy within Company X. It explores the relationship between data quality and the ability to leverage data for informed decision-making and proactive maintenance planning. By improving data quality, Company X can rely on accurate and reliable data to drive maintenance activities, moving away from reactive approaches based solely on budgetary considerations. Answering this research question will provide valuable insights into the benefits and challenges associated with adopting a data-driven maintenance approach, enabling Company X to make informed decisions regarding their maintenance strategy and improve overall operational efficiency.

2.0 Methodology of Tackling the Outlined Research Questions

In this chapter, our focus is on identifying the methods that will be utilized in the application chapters to address each sub-research question. The primary objective of this chapter is to carefully select the most appropriate methods from this section to effectively tackle each sub-research question. By aligning the chosen methods with the specific requirements of each question, we aim to provide comprehensive and insightful answers in the subsequent chapters.

The significance of this chapter lies in its role as a bridge between the research questions and the practical application of methods. It serves as a critical step in formulating an appropriate methodology for each sub-research question, ensuring that the subsequent chapters are guided by a systematic and well-suited approach.

2.1 General Problem-Solving Methodology

The problem-solving methodology conducted in this study aims to address the main research question as well as the complementing sub-research questions. By adopting a systematic approach, the key aspects of the research question can be explored. In this research, the Managerial Problem-Solving method will be the main systematic problem-solving approach utilized. As shown in Figure 5 below, the MPSM involves 7 phases. Phase one, defining the problem has already been conducted in section 1.1, where a problem cluster followed by the core and action problems have been identified.

Figure 5: MPSM

In this section, phase 2 of the MPSM will be tackled, where the method employed to answer the main research question will be outlined, followed by the description of four additional methods utilized to address the complementing sub-research questions.

By carefully evaluating and selecting the methods presented in this chapter, we can establish a solid foundation for addressing each sub-research question in a robust and reliable manner. The identification and selection of methods specifically tailored to each question will facilitate the acquisition of relevant data, analysis, and interpretation, leading to meaningful insights and conclusions.

To ensure a clear understanding of the approach and serve as a comprehensive summary of this chapter, a table is presented below. This table illustrates how each research question is addressed using the corresponding methodology and the respective MPSM phase, intended use, research population, and where the corresponding answer can be found. After the table, the data gathering methods outlined would in the table be explained.

Sub-Research Question (SRQ)	MPSM Phase	Data Gathering Method	Research Population	Intended Use	Covered In
SRQ 1 - How is Company X's asset data made, used, and stored?	**1,3**	Method 1: Interviews Method 2: Internal Observations	Stakeholde rs Company Database	Context Analysis	Chapter 3
SQR 2 - What are the current data quality issues faced by Company X that hinder the transition to a data-driven maintenance strategy?	**3**	Method 1: Interviews Method 2: Internal Observations	Stakeholde rs Company Database	Context Analysis	Chapter 3
SRQ 3A – How can the current situation be assessed and measured?	**3**	Method 2: Internal Observation Method 3: Literature Review	Company Database Academic Database	Context Analysis	Chapter 3
SRQ 3B+C – What method is best to match the existing mismatched assets and update the data? How can the updated asset data be assessed for reliability?	**4,5,6**	Method 3: Literature Review Method 4: Expert opinion	Academic Database (Scopus, Google Scholar) Expert	Solution Generation	Chapter 4
4 – How can Company X prevent the reoccurrence of un-reliable asset data?	**4,5**	Method 3: Literature Review Method 4: Expert opinion	Academic Database (Scopus, Google Scholar) Expert	Solution Generation	Chapter 5
SRQ 5 - How can the improvement of data quality contribute to reducing maintenance costs, minimizing equipment downtime, and optimizing resource allocation at Company X?	**6,7**	Method 3: Literature Review Method 4: Expert opinion	Academic Database (Scopus, Google Scholar) Expert	Solution Generation + Solution Validation	Chapter 6 Chapter 7
SRQ6 - How can the improvement of data quality contribute to the transition from budget-based maintenance to data-driven maintenance?	**6,7**	Method 3: Literature Review Method 4: Expert opinion	Academic Database (Scopus, Google Scholar) Expert	Solution Validation	Chapter 6 Chapter 7

Table 1: Chapter Summary : Sub-Research Questions Tackling Plan

2.2 Research Data Collection Methods

To answer each sub-research question, their exists multiple data collection methods to answer each of them.

2.2.1 Method 1: Interviews

This method takes a face-to-face approach by communicating with relevant stakeholders in the company to hear the issue from their side. The selected interview subjects would be maintenance plant managers. They are responsible for all maintenance activities in the plant, where all struggles and points of improvement the plant faces regarding asset data reaches the plant maintenance manager. Hence, they are perfect interview subjects to speak with as they have all the required information. The aim of this method would be understanding the situation better from a stakeholders' perspective, to make valid and reliable conclusions in this thesis. Moreover, a set of interview questions was designed:

1. Data Quality Assessment:
A. How would you rate the current quality of maintenance data within the plant?
B. What specific issues or challenges have you encountered with the quality of maintenance data?
C. Can you provide examples of instances where poor data quality has hindered decision-making or maintenance operations?

2. Root Causes of Poor Data Quality:
A. What do you believe are the main reasons for inaccurate or incomplete data recording in the maintenance processes?
B. Have you identified any challenges in data collection, validation, or entry that affect data quality?
C. Are there current methods or practices that ensure data validity? By you or from corporate.

3. Current Data Improvement Strategies:
A. What steps or actions are being taken to fix the current mismatch and quality of maintenance data?
B. Are you going to physically check each asset or are there any specific tools, technologies, or processes that you are using now?

4. Data Integration and Standardization:
A. How are different sources of maintenance data currently integrated and consolidated?
B. Are there any data standardization practices or protocols in place to ensure consistency across systems or departments?

5. Data Collection and Recording Practices:
A. How are maintenance data collected and recorded currently? Are there any challenges with these practices?
B. Are there any specific training or guidance provided to employees regarding data collection and recording?
C. What measures can be implemented to encourage employees to maintain accurate and consistent data collection?

6. Data Access and System Usage:
A. What complications has the plant faced when attempting to access and retrieve the required data for decision-making purposes?
B. Has the plant taken preventative steps to enhance data accessibility and promote its effective usage?

7. Preventive Measures for Future Data Quality:
A. Do you think that a standardized decision-making flowchart for new assets t is a viable solution to prevent this issue in the future?
B. What other strategies or processes can be implemented to prevent the recurrence of poor data quality issues in the future?
C. How can continuous monitoring and quality control be integrated into the maintenance data management process?

Figure 6: Interview Questions

Validating responses: What if two responses are different?
It may occur that two different maintenance plant managers have different results. However, in these questions, there is no right or wrong answer, it is all about perspectives and the fact that each production plant has unique circumstances adds to that. However, if I feel something is too out of

scope, I will investigate that using academic literature review and discuss it with a trusted high managing stakeholder, and rely on his seniority and expertise.

Codes and Themes saturation: The number of needed interviews:
Determining when to stop conducting interviews in research and identifying the optimal number of interviews depends on various factors, including the research objectives, data saturation, and resource constraints. While there is no fixed rule, considering ethical considerations and thematic saturation can help guide this decision.

Ethical considerations: Researchers should ensure they respect the rights and well-being of participants. This means that interviews should be conducted in a manner that minimizes any potential harm or discomfort to participants. If interviews continue to yield similar insights and data without providing significant additional value, it may be appropriate to conclude the interview phase.

Thematic saturation: Thematic saturation refers to the point in data collection where new interviews are no longer providing new or substantial insights or themes. It implies that the researcher has achieved a sufficient understanding of the research topic and that additional interviews are unlikely to yield substantially different information. This saturation point can vary depending on the complexity of the research topic and the heterogeneity of the sample.

2.2.2 Method 2: Internal Observations

This method is acts as an informal approach to gain further knowledge on how the company operates. This method is based on individually observing the existing process using the resources provided to me by the company. Some examples are:

1. **SAP**: is the ERP system used in Company X. Most processes are conducted in SAP. Looking at Figure 7 in the next page, using my provided company laptop with access to SAP, I can open SAP and investigate existing assets. More specifically looking into what data sets exist in SAP for each asset so I can gain a better understanding of asset data and what attributes would be needed to take in mind when investigating the existing data quality issue in the company.

2. **Work-related office discussions:** This method goes over the method of gaining information of the situation using informal everyday office communication like weekly progress meetings with my team or the production plants or casual talks with my manager about the situation. This tool is the greatest source of knowledge, as it contains the highest frequency of occurrence.

3. **Company file database:** The company has provided me access with a database that contains the outline of many of the existing processes in the company. This would be another form of data acquisition. Rather than going through SAP and communicating with stakeholders, I can get some of the information I need straight from company files. An example of this is a process map of how an asset gets assigned a criticality.

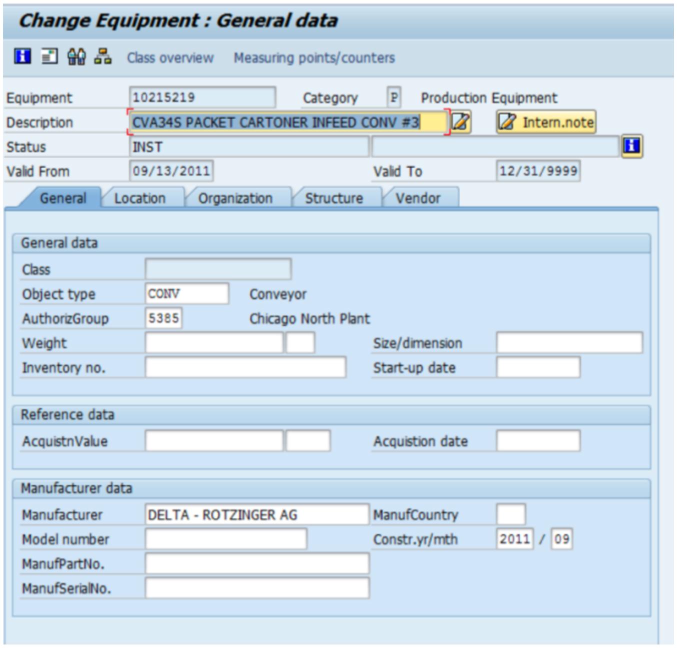


Figure 7: SAP Asset Data Example

2.2.3 Method 3: Literature Review

A literature review involves systematically searching, analyzing, and synthesizing existing literature relevant to the research question. This approach has several benefits, including giving a thorough grasp of the subject, finding knowledge gaps, and gathering perspectives from experts in the field and will act as the main solution generation method in this project. The procedure for doing a literature review for this study is summarized as follows:

1. **Identification of relevant literature:**
   - Find important databases, scholarly publications, business publications, and conference proceedings that are related to asset data quality and maintenance decision-making.
   - Create a search plan utilizing relevant keywords and phrase combinations.
   - Obtain a wide selection of literature on the topic of the study issue.
2. **Selection and screening:**
   - Evaluate the retrieval of material for its applicability to the study issue.
   - Check the titles and abstracts of articles to see if they should be included.
   - Don't include unrelated or unreviewed sources.
   - Choose the best-written, most relevant material for future study.
3. **Extraction and analysis of data:**
   - In-depth reading and analysis of the chosen literature should be done with an emphasis on the necessity of accurate and trustworthy asset data for maintenance decision-making.
   - Extract the most important ideas, hypotheses, and conclusions linked to the study subject.
   - Create themes or categories from the retrieved data for easier comprehension and comparison.
4. **Discussion and synthesis:**
   - Summarize the results of the literature review, emphasizing the most important discoveries, patterns, and trends.
   - Examine the literature's parallels, divergences, and inconsistencies to spot knowledge gaps and potential study fields.

- Discuss the consequences of the research findings for the asset data quality issue at Company X and how it affects maintenance choices.
- Based on the results of the literature analysis, suggest improvements to maintenance procedures and the quality of asset data.

2.2.4 Method 4: Expert Opinion

Seeking expert opinion involves engaging with individuals who possess significant experience and expertise in a particular field. In this case, an engineer with 35 years of experience in the manufacturing industry, and 20 years of managerial experience, his experience allows him to have a very knowledgeable opinion on issues in the industry. His expertise would act as a validation method for the findings of this project. Here is an outline of the steps involved in utilizing expert opinion as a method of data acquisition:

1. **Establishing Contact:**

- Establish communication: discuss the research objectives and the specific problem of asset data quality at Company X's production plants.
- Seek his willingness to provide expert opinions and insights for the research.

2. **In-depth Verbal Contact:**

- Prepare: Gather the needed questions or insights and the relevant material.
- Brief: Brief the expert on the current situation
- Ask: Ask the expert

3. **Analysis and Integration:**

- Thoroughly analyze the information gathered from the interviews, focusing on key themes, perspectives, and recommendations provided by the expert.
- Identify commonalities, discrepancies, and patterns within the expert's opinions and insights.
- Integrate the expert's opinions and insights with other data sources, such as the literature review and quantitative data, to provide a comprehensive understanding of the asset data quality problem.

4. Validation and Cross-Referencing:

- Validate the expert's opinions and insights by comparing them with other relevant sources of information, such as industry reports, scholarly articles, and best practices.
- Cross-reference the expert's opinions with the findings from other data acquisition methods to ensure consistency and reliability.

3.0 Context Analysis

This chapter of the thesis focuses on conducting a comprehensive context analysis of Company X's asset data management practices. The following sub-research questions, SRQs 1abc + 2ab + 3a, are designed to provide a thorough understanding of the current state of asset data within the organization. The findings of these questions would provide valuable insight into Company X's data structuring methods. Furthermore, this section aims to identify the data quality issues that hinder Company X's transition to a data-driven maintenance strategy. It will explore dimensions such as accuracy, completeness, and consistency that may be lacking within the company's data infrastructure, along with the root causes of these issues, such as data entry errors, system integration challenges, or a lack of data validation processes.

Understanding the impact of these data quality issues on Company X's decision-making and maintenance strategies is necessary for the solution formulation process of this thesis. Even though some of the findings are not directly related to addressing the issue of asset criticality data, these findings add valuable insight into understanding broader scopes of the issue, which will play a significant role in researching solutions to our core asset criticality data issues. Additionally, this context analysis will address the issue of mismatched asset data across multiple data sources, exploring methods to assess and measure the current situation. By delving into these research questions, a comprehensive foundation will be established, providing the necessary insights to guide subsequent chapters of the thesis.

Starting with gaining insight into Company X's asset data types and usages, sub-research question 1, shown below, would be tackled first.

How is Company X's asset data made, used, and stored?

3.1 Data Types

This section aims to first identify the types of asset data in Company X, to provide a solid framework for the work that follows, one must comprehend all the different types of asset data at Company X.

What type of asset data exist?

The maintenance departments of production plants necessitate continuous access to data for their operations. Making maintenance decisions relies heavily on various types of equipment data. It is crucial to identify these distinct data types as they form a robust foundation for the problem-solving approach. The research employs methods such as interviews and internal observations to derive the answers presented below. Answering these sub-research questions is a part of the 3rd phase of the MPSM process, which involves analyzing the problem. The findings are as follows:

1. **Equipment Criticality:** Each asset is assigned a criticality that reflects its importance in the production process. Where this data helps prioritize maintenance activities and allocate resources accordingly. Factors such as impact on production lines, safety implications, downtime costs, and regulatory compliance are considered in determining equipment criticality.

2. **Failure History:** Compiling information on previous equipment failures, including their frequency, underlying causes, and effects. This information helps in recognizing typical failure modes, comprehending failure trends, and creating suitable maintenance plans to avoid more failures.

3. **Maintenance Records:** Keeping track of all prior maintenance actions, such as work orders, inspection reports, and maintenance schedules. Through improved planning, expense tracking, and assuring adherence to maintenance plans, this data offers a historical view of maintenance activities. A historical view allows maintenance management to take reliable decisions based on data collected from past maintenance events. However, as this method provides factual data, the difference in circumstances between the past and the present should be taken into account; hence, stakeholders should not treat historical data as an independent, sufficient method.

4. **Monitoring:** Data from condition monitoring devices mounted on equipment, such as temperature, pressure, vibration, or wear measures, are collected in real-time. This information makes it possible to use predictive maintenance strategies, spot deviations from the expected operating parameters, and continuously monitor the health of the equipment.

5. **Performance Metrics:** Compiling information on metrics for measuring the performance of equipment, including uptime, downtime, MTBF, MTTR, and overall equipment effectiveness OEE. These measurements aid in assessing the effectiveness of the equipment, pinpointing potential problem areas, and enhancing maintenance plans.

6. **Test and Inspection Results:** recording data, observations, and conclusions from tests and inspections. This information assists in evaluating the state of the equipment, seeing possible problems or degradation, and figuring out what maintenance is necessary.

7. **Manufacturers' maintenance recommendations:** Use the instructions, manuals, or specifications provided by the equipment's manufacturer to find out about suggested maintenance tasks, check-in cycles, and part replacement dates. This information guarantees adherence to manufacturer guidelines and improves the dependability and performance of equipment.

8. **Lubrication and Fluid Analysis:** Monitoring information about the lubricants, oils, and fluids used in equipment is known as "*lubrication and fluid analysis*." These learnings aid in enhancing lubrication procedures, spotting possible problems, and avoiding equipment breakdowns.

9. **Energy Consumption:** Gathering information on *energy consumption* related to equipment operation. This information aids in locating possibilities for energy savings, tracking equipment effectiveness, and streamlining maintenance procedures to enhance energy performance.

These kinds of equipment data may be used by maintenance departments to make data-driven choices, proactively identify maintenance requirements, optimize resource allocation, decrease downtime, increase equipment dependability, and improve overall operating efficiency in the manufacturing plant.

3.2 Data Storage

This section explores the different areas of data storage in Company X. Answering this question would provide better understanding of where the asset data mismatch occurs from and in which source.

Where is it stored?

The Systems Applications and Products software in Company X, plant lists, and physical data are generally the three major sources of equipment data for the maintenance division of a manufacturing facility. Each source provides useful data to use with maintenance decision-making:

1. SAP: In industrial settings, an integrated software program called SAP is frequently used to handle several corporate functions, including maintenance. Numerous pieces of equipment data, including work orders, service histories, spare parts inventories, maintenance schedules, and expenses, are stored and managed by SAP. It gives maintenance managers access to a centralized library of structured data to track and evaluate maintenance operations, expenses, and performance measures. Planning, resource allocation, and reporting for maintenance activities are made possible by SAP data.

2. Plant Lists: Plant lists refer to detailed inventories of equipment and assets within the production plant. These lists often contain facts about the equipment, such as its characteristics, identifying numbers, and location. An overview of the equipment landscape provided by plant lists enables maintenance managers to gauge the size and difficulty of the maintenance activities. They support the development of maintenance plans based on the asset portfolio of the plant, the identification of important equipment, and the determination of maintenance priorities.

3. Physical Inventory: Through inspections, measurements, and evaluations, physical data is information that is gathered directly from the equipment and its parts. Data obtained from visual inspections, condition monitoring systems, sensor readings, and specialized testing are included in this. Physical data offers real-time or nearly real-time information into the equipment's state, functionality, and health.

Maintenance managers may get a thorough understanding of the equipment ecosystem by using data from these three sources. Matching asset data across these three sources creates a reliable data set that can be used by the maintenance managers to make data-driven decisions, meaning the ability to peruse more efficient recourse allocation across the asset's maintenance activities. For example, by prioritizing the asset in the data (criticality assessment, Appendix A), stakeholders can identify the needed effort for each asset, which results in a less total cost per asset. Through the integration of these three data sources, maintenance decision-making can be approached holistically, resulting in increased operational effectiveness, less downtime, and improved asset management in the manufacturing facility.

3.3 Data Usage

This section discusses the different asset data usages within Company X:

How is it used?

The production plant's maintenance department uses the equipment data described previously to influence judgements about maintenance tasks. Here is how each sort of data affects how decisions are made:

1. **Equipment Criticality**: Maintenance managers may prioritize maintenance activities based on the equipment's influence on productivity, safety, and costs by determining the criticality of the equipment. The attention and resources given to high-criticality equipment increase the likelihood that maintenance tasks will be in line with corporate objectives.

2. **Failure History:** Examining previous equipment failures enables the identification of typical failure mechanisms and underlying causes. With the use of this knowledge, maintenance managers may create plans to reduce or stop similar failures in the future. It enables the application of reliability-centered maintenance (RCM) techniques and tailored maintenance operations.

3. **Real-time data:** from sensors and monitoring systems may be used to get knowledge about the condition and functionality of equipment. The status of the equipment may be continually monitored to identify any changes from the typical operating conditions. The capacity to schedule maintenance based on the actual state of the equipment, minimizing downtime and maximizing availability, improves decision-making.

4. **Equipment Performance Metrics:** Uptime, downtime, MTBF, MTTR, and OEE are examples of performance metrics that offer a quantitative evaluation of an item's efficacy and efficiency. These indicators aid in pinpointing problem areas, establishing performance goals, and directing choices on upkeep tactics, equipment replacement, or process enhancement.

6. **Inspection and Test Results:** Information from inspections and testing reveals vital details about the state of the equipment and identifies any possible problems. These findings can be used to inform choices about repairs, component replacements, and modifications to maintenance schedules. Based on known hazards, this information aids in prioritizing maintenance tasks.

7. **Manufacturers' Recommendations for Maintenance:** Equipment manufacturers offer suggestions and instructions for maintenance tasks. By following these suggestions, you can make sure that your maintenance choices are in line with industry standards, warranty requirements, and factors unique to your equipment.

8. **Analysis of Lubricants, Oils, and Fluids:** Monitoring lubricants, oils, and fluids by analysis aids in the discovery of anomalous circumstances, contamination, or degeneration. Making decisions include modifying lubrication procedures, carrying out preventative maintenance procedures (such as fluid replacement and filter replacements), or taking care of prospective problems before they result in equipment breakdowns or performance deterioration.

8. **Energy Consumption Data:** Keeping track of energy consumption data reveals chances to increase energy efficiency and cut costs. Making decisions may involve finding energy-saving projects, improving maintenance procedures to reduce energy consumption, or putting newer, more energy-efficient equipment into operation.

9. **Historical Data and Trend Analysis:** Predictive maintenance techniques are made possible by analyzing past data and spotting trends. Decisions on maintenance can be made proactively by using past patterns and trends. It is possible to create predictive maintenance models, enabling maintenance procedures to be carried out before.

In general, these equipment data sources help the maintenance staff make decisions based on data. Maintenance managers can prioritise maintenance work, efficiently schedule maintenance activities, optimise resource allocation, reduce downtime, and generally increase the dependability and efficiency of the manufacturing plant by taking these numerous data types into account.

3.4 Maintenance Strategy Transition Bottlenecks

This section explores the current data infrastructure and data quality issues faced by the department.

What are the current data quality issues faced by Company X that hinder the transition to a data-driven maintenance strategy?

Significant inconsistencies in asset data between the three current sources—SAP, individual plant data lists (Excel), and physical assets—are the core Company X's current data quality problems. The shift to a data-driven maintenance plan is hampered by these differences, which conclude none of the three sources trustworthy for making decisions.

What specific data quality dimensions (e.g., accuracy, completeness, consistency) are lacking within Company X's current data infrastructure?

The present data infrastructure at Company X has problems with accuracy, completeness, and consistency of the data. The disparities in data between the sources point to insufficient data records, inaccurate asset criticality rankings, and inconsistent asset information between systems. As shown in Figure 8, a lot of required asset data is missing and incomplete, which is an indicator of a lack of standardization of asset data filling. In Figure 8 below, an illustration has been formulated, acting as an example of incomplete data within Company X, where several inconsistencies with the data have been highlighted.

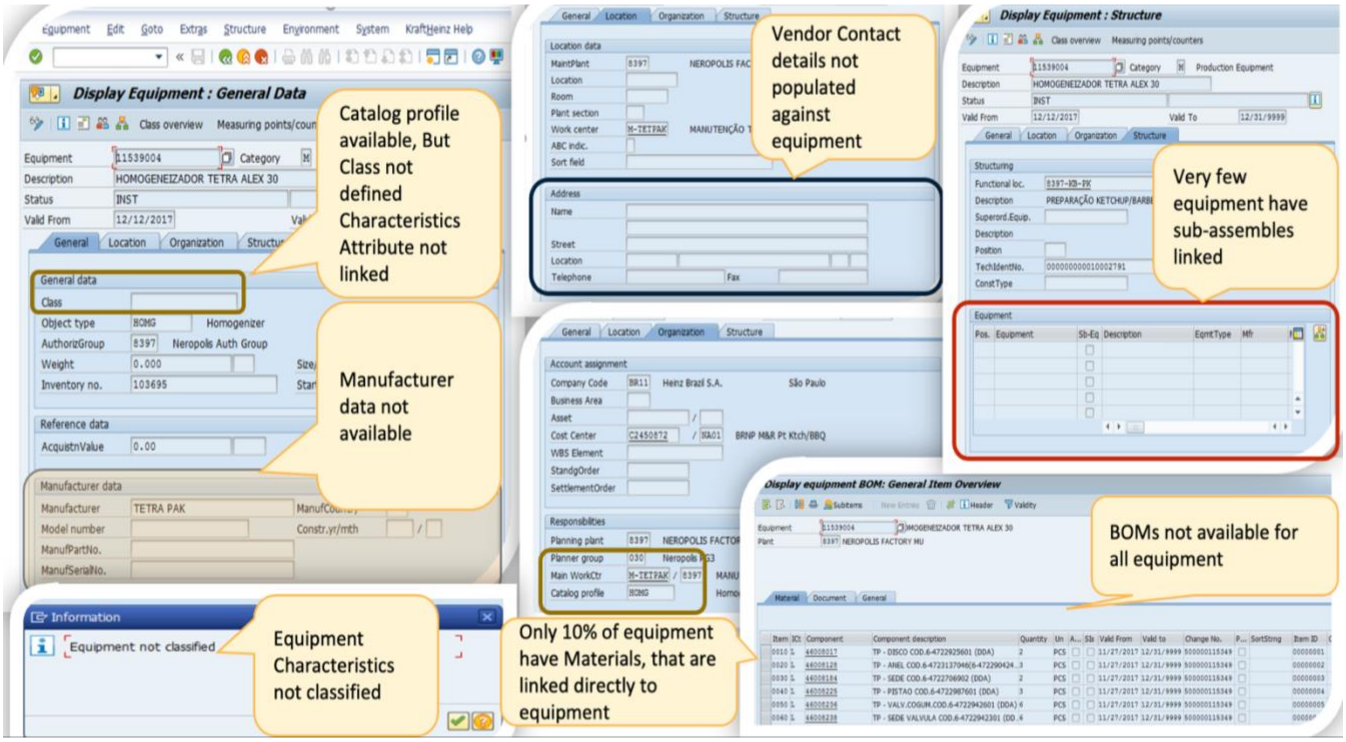


Figure 8: Asset Data Incompleteness

What are the root causes of these data quality issues, such as data entry errors, system integration challenges, or lack of data validation processes?

The data quality problems at Company X can be attributed to several factors. One significant issue arises from data entry mistakes made during manual data entry into the systems. This means that when employees manually enter asset data, errors and typos can occur, leading to inaccuracies in the information.

Another factor contributing to the data quality problems is the difficulties in integrating data from various sources. Company X might have data stored in different databases or formats, making it challenging to consolidate and synchronize information effectively. As a result, inconsistencies may arise when trying to merge data from different sources.

Additionally, the absence of effective data validation procedures further compounds the data quality problems. Data validation involves performing checks and tests on the data to ensure its accuracy and reliability. Without proper validation processes in place, erroneous data might go undetected, leading to data quality issues.

How do these data quality issues impact Company X's ability to make informed decisions and implement proactive maintenance strategies?

Company X's ability to execute preventative maintenance methods and make educated judgements is significantly impacted by the data quality concerns. The appropriate assessment of asset criticality is hampered by inaccurate and inconsistent data, which results in a surplus of spare parts inventories, wasteful maintenance orders, and improper resource allocation. This has an impact on the business's capacity to assign suitable maintenance plans, optimise maintenance frequency, and efficiently manage labour resources. Efficiency and cost-effectiveness are hampered by the inability to switch from a budget-based maintenance approach to a data-driven strategy due to a lack of trustworthy data.

To allow informed decision-making, improve maintenance plans, optimise resource allocation, and ease the shift to a data-driven maintenance strategy, Company X's asset data infrastructure must be improved.

4.0 Application: Fixing current asset criticality data mismatch.

This is a transitioning point of this thesis, where the coming sub-research questions (3b-4-5-6), shift towards the aims of solution generation and investigation. The mentioned sub-research questions are correspondingly tackled in the coming chapters (4-5-6-7). The chapters aim to address the core problem of present and futuremismatched asset criticality data in Company X and provide viable solutions to resolve the issue. After identifying solutions for the present and the future of Company X, the chapters then go on to explore the potential benefits of improving data quality in terms of reducing maintenance costs, minimizing equipment downtime, and optimizing resource allocation at Company X. Furthermore, they dive into how the improvement of data quality can contribute to the transition from a budget-based maintenance approach to a more data-driven maintenance strategy. By addressing these research questions, critical methodologies and tools will be identified to match the existing mismatched assets, update the data, and ensure the future reliability of the updated asset information with academic research supporting our findings. Moreover, the chapter will explore how proper data collection methods and management practices can be implemented to maintain the quality and consistency of data attributes. Overall, this chapter provides a comprehensive understanding of the impact of data quality improvement and its potential benefits, serving as a crucial step toward enhancing asset management practices within Company X.

In this chapter, sub-research question 3b presented below will be investigated. Using selected literature techniques and expert opinion recommendations, the methodology for fixing the current asset data mismatch across SAP and the Plant lists will be formulated in this section. The aim of identifying this methodology would be communicating this methodology to the production plants to be applied to resolve the mismatch, where the results of this application would be discussed in the results chapter of this research paper.

How can Company X solve their current issue of mismatched asset data across multiple data sources?

What method is best to match the existing mismatched assets and update the data?

The need for tackling this question stems from the significant impact inaccurate or inconsistent asset data can have on various aspects of the organization's operations. Accurate asset information is essential for making well-informed decisions, conducting efficient maintenance, and allocating resources effectively. Company X has encountered a challenge where assets' criticality, characteristics, or other relevant information stored in different datasets, such as SAP and the Plant List, do not align. This misalignment has resulted in mismatched assets, where crucial asset details differ or are not synchronized between the datasets. Addressing this issue is vital for ensuring reliable asset management practices, optimizing data-driven decision-making, and enhancing overall operational efficiency. Therefore, the focus now lies on determining the most suitable method to match the existing mismatched assets and update the data, thus establishing a cohesive and reliable foundation for improved asset management at Company X.

Before explaining the methodology and discussing the application in detail, the figure below is a brief summary of the formulated processes of fixing the current asset mismatch:

Figure 9:Fixing current mismatch process summary

4.1 Methodology

Using expert opinion by the chosen expert in this study as well as head of global maintenance, a framework to answer this research question has been formulated into 3 steps that will be discussed below and are aimed to gather a clean, assessable as a solid baseline to able to match relevant data sets when the solution is applied or else the solution would be unapplicable:
Data Cleansing → Three-way data check → Physical Check.

4.1.1 Data Cleansing

The first step in addressing the problem of data mismatch across multiple sources (SAP and Plant lists) is to obtain two comparable data sources. It's crucial to understand that the procedure entails more than just pasting the data sets into an Excel sheet and comparing them according to presumptions.

Most importantly, data sets must be compatible, which means having similar structures and parameters. This results in better comprehension of the underlying data.

Furthermore, it is crucial to define precise criteria and rules for figuring out the level of resemblance or matching between the data sets in addition to ensuring that parameters and structures are compatible. This entails identifying the precise data fields or features that need to line up as well as considering any conversions or transformations that might be required to achieve compatibility.Organizations build a solid basis for dealing with data mismatch issues and enhancing the overall integrity and dependability of their data sources by guaranteeing compatibility and specifying criteria for matching.

According to (Agusthiya et al, 2014) the way to achieve a sufficient baseline of two comparable data sources, data cleansing should be the first step. Where they formulated an educated framework for data cleansing that can be used across multiple industries.
The data cleansing process is as follows:
1. Selection of tables from multiple data sources
2. Selecting each attribute in the table and formatting the attributes.
3. Match each table column to the final table column.
4. Joining all the tables.
5. Create Tokens and to find duplicates through tokens

6. Ranking: After finding duplicates, we rank the columns according to the uniqueness of the value 7. Removing duplicates according to the rank 8. Finally get the cleaned data then store in the database. (Agusthiya et al, 2014)

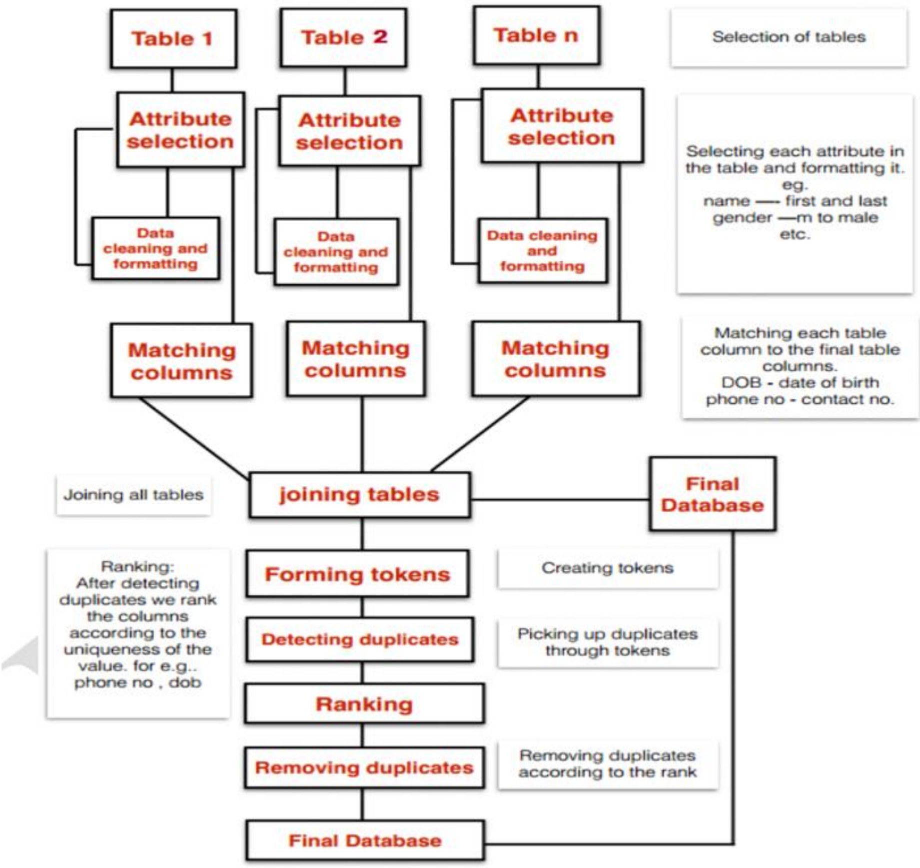


Figure 10:Data Cleansing Methodology (Agusthiya et al, 2014)

4.1.2 Three-way data check

This an essential step for the solution process, comparing the data sets would give one a clear understanding of the gaps that need to be filled in Company X's asset data sources. A selected number of academic literatures was selected to further support our method to tackle current asset data mismatch.

The first literature goes on to say that assets can be tangible (physical) or intangible (knowledge-based) resources that enhance a company's capacity (Jugdev et al, 2007). The physical inventory in the context of asset management in a manufacturing represents the physical assets existing in the factory. You may confirm the presence and state of the factory's assets by checking the physical inventory.

Second, it is acknowledged that using data infrastructures for asset management is a crucial component of asset management practices. The development of data infrastructures in the context of asset management organizations is covered by (Brous et al, 2019). They contend that data infrastructures ought to be thought of as complex adaptive systems (CAS) that are capable of changing over time. In essence, one is checking the plant's data infrastructure to make sure that the information from various sources is reliable and compliant.

The literature also emphasizes the use of big data technology for asset condition information management. The value of big data analytics in enhancing asset management decision-making is emphasized by McMahon et al. (2020). Although they focus on the requirements and difficulties of using big data analytics in railway asset management, the concepts are transferable to asset management in other sectors. You can make sure that the data from various sources is correct and trustworthy, which is essential for making efficient asset management decisions, by doing a three-way data check.

The idea of asset tracking is also covered in the literature. A method for automated asset tracking in data centers utilizing a mobile robot with vision is described by Nelson et al. (2013). They emphasize the need of precisely tracking asset layout in order to carry out administration and optimization duties. You may track and verify the factory's assets by doing a three-way data check, which verifies that the data from various sources agrees with the physical world.

The main takeaway from the text is that conducting a thorough comparison and analysis of asset data sets is a crucial step in the solution process for addressing asset data gaps in Company X. The text highlights the importance of academic literature to support the methodology in tackling the current mismatch in asset data. Conducting a thorough comparison and analysis of asset data would confirm the data gap that needs to be filled and express the need for a physical check.

4.1.3 Physical Audit

A physical verification of the assets is necessary to ensure data consistency and dependability between the SAP system and the manufacturing plant's list. As the two existing data sources (SAP vs Plant List) mismatch, one cannot use either as a reliable decision-making data source, as one does not know which is right. Hence, only the physical assets seem to be the sole reliable source that can portray what is real and what is not. The manufacturer can get precise information right from the assets themselves by doing a complete physical inspection. This physical verification procedure will act as a trustworthy guide to fix the errors in the current data sources.

Utilizing simply the SAP system or the production plant's data list will only increase the current problems with data quality. Thus, in light of the plant’s current situation, a thorough solution to the data quality problems relating to their assets is required. A comprehensive physical inspection of the assets is the only practical way to ensure consistency and dependability between the SAP system and the list of the manufacturing facility. To correct the errors in the current data sources, this physical verification procedure will act as a trustworthy reference point, paving the path for higher data quality and informed decision making.

The outlined method of physical data check has been researched in literature to support this finding, where numerous academic sources support the methodology of this process and highlight the fact that a physical check is necessary. The supporting literature findings are:

Boyer & Lewis (2009) discusses the concept of competitive priorities in operations strategy. It emphasizes the need for trade-offs in operations strategy and highlights the importance of quality, dependability, and low costs. This supports the idea that physical verification of assets is necessary to ensure data consistency and dependability between the SAP system and the manufacturing plant's list.

Laseter & Ramdas (2002) explores the relationship between quality management information (QMI) and operational performance in manufacturing plants. It explores the importance of communication, integration, and information sharing methods in improving operational performance, which supports the idea that physical verification of assets can provide accurate information about the condition, location, and characteristics of each asset, which can then be used to synchronize the datasets and enhance data quality.

Belić et al. (2019) discusses the use of data-driven root cause analyses in multistage manufacturing. It highlights the importance of managing dimensional quality and improving product geometry. This supports the idea that physical verification of assets can help identify errors in the current data sources and provide a reliable benchmark for future decision-making procedures.

Banker et al. (2006) discusses the role of plant information systems in manufacturing capabilities and plant performance. It emphasizes the importance of real-time exchange of production and demand data within and across manufacturing plants. This supports the idea that physical verification of assets can help update and synchronize the asset data between the SAP system and the manufacturing plant's list, leading to improved plant efficiency.

Overall, these scholarly sources provide support for the methodology of conducting a physical verification of assets to ensure data consistency and dependability between different data sources. They highlight the importance of accurate asset data for decision-making, operational performance, and overall plant efficiency. By conducting a thorough physical inspection, the plant would finally poses a 100% reliable data set that can then be matched to the other data sets as a reliable reference.

4.2 Application

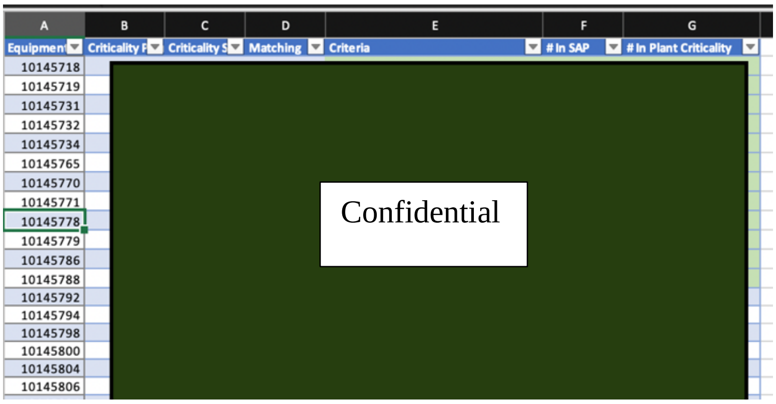
Using the literature supported methods outlined above, I have conducted a thorough data analysis to further explore the current state of the assets, which was briefly discussed in the section: Norm Vs Reality. In this section, my step-by-step methodology would be explained.

4.2.1 Data Analysis

The aim of this data analysis is to compare, for each asset, the criticality (Appendix A) assigned to it in SAP versus the plant's physical asset list.

The takeaway sought from this analysis would be confirming the theory that assets are significantly mismatched between the two data sets.

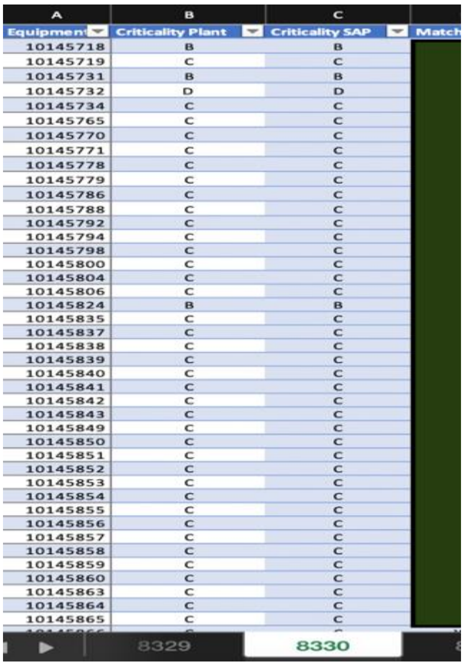
1. **Data Cleansing:** The initial phase of the analysis focuses on data cleansing to ensure a reliable and consistent dataset. The objective is to identify assets that exist in both SAP and the Plant List while excluding any assets that do not have corresponding entries in both datasets. This step ensures that only assets with matching information are included in the subsequent analysis. The identification of such assets that exist in both datasets is communicated to the management, and assets that do not match are excluded from further analysis.



Equipment	Criticality P	Criticality S	Matching	Criteria	# In SAP	# In Plant Criticality
10145718	[redacted]					
10145719						
10145731						
10145732						
10145734						
10145765						
10145770						
10145771						
10145778						
10145779						
10145786						
10145788						
10145792						
10145794						
10145798						
10145800						
10145804						
10145806						

Figure 11: Plant Z Merged Asset List

2. **Merging Data:** Before proceeding to the extraction of criticality values, a crucial step involves merging the identified compatible asset list from both SAP and the Plant List datasets. This merging process combines the relevant asset information from both sources into a matching dataset. By merging the data, a unified view of the identified compatible assets is established, facilitating easier analysis and comparison of criticality values. Figure 11 showcases the results of the selected plant, Plant Z.



Equipment	Criticality Plant	Criticality SAP	Match
10145718	B	B	[redacted]
10145719	C	C	
10145731	B	B	
10145732	D	D	
10145734	C	C	
10145765	C	C	
10145770	C	C	
10145771	C	C	
10145778	C	C	
10145779	C	C	
10145786	C	C	
10145788	C	C	
10145792	C	C	
10145794	C	C	
10145798	C	C	
10145800	C	C	
10145804	C	C	
10145806	C	C	
10145824	B	B	
10145835	C	C	
10145837	C	C	
10145838	C	C	
10145839	C	C	
10145840	C	C	
10145841	C	C	
10145842	C	C	
10145843	C	C	
10145849	C	C	
10145850	C	C	
10145851	C	C	
10145852	C	C	
10145853	C	C	
10145854	C	C	
10145855	C	C	
10145856	C	C	
10145857	C	C	
10145858	C	C	
10145859	C	C	
10145860	C	C	
10145863	C	C	
10145864	C	C	
10145865	C	C	

Figure 12: Extracted Criticalities

3. **Extraction of Criticality Values:** With the merged dataset of compatible assets, the next step involves extracting the criticality values associated with each asset from the respective datasets. This is accomplished by utilizing a combination of Excel functions, specifically the VLOOKUP function, to retrieve the criticality values from both SAP and the Plant List datasets. The VLOOKUP function allows for the retrieval of data from one dataset based on matching criteria from another dataset. As seen in Figure 12, criticalities have been extracted for all matching assets.

Equipment	Criticality Plant	Criticality SAP	Matching	Criteria	# In SAP	# In Plant Criticality
10145718	B	B	YES	A		
10145719	C	C	YES	B		
10145731	B	B	YES	C		
10145732	D	D	YES	D		
10145734	C	C	YES	E	Confidential	
10145765	C	C	YES	Total ABC		
10145770	C	C	YES	Total DE		
10145771	C	C	YES	No Criticality (=#N/A)		
10145778	C	C	YES	% of Assetts with no Criticality in SA		
10145779	C	C	YES	Total # of mismatches		
10145786	C	C	YES	Total # of Assets		
10145788	C	C	YES	% of Mismatched Assets	=	2,02
10145792	C	C	YES			
10145794	C	C	YES			
10145798	C	C	YES			
10145800	C	C	YES			
10145804	C	C	YES			
10145806	C	C	YES			
10145824	B	B	YES			
10145835	C	C	YES			
10145837	C	C	YES			
10145838	C	C	YES			
10145839	C	C	YES			
10145840	C	C	YES			
10145841	C	C	YES			
10145842	C	C	YES			
10145843	C	C	YES			
10145849	C	C	YES			
10145850	C	C	YES			
10145851	C	C	YES			
10145852	C	C	YES			
10145853	C	C	YES			
10145854	C	C	YES			
10145855	C	C	YES			
10145856	C	C	YES			
10145857	C	C	YES			
10145858	C	C	YES			
10145859	C	C	YES			
10145860	C	C	YES			
10145863	C	C	YES			
10145864	C	C	YES			

Figure 13: Quantitative Assessment of Plant Z

4. **Quantitative Assessment:** Having obtained the criticality values for each asset from both SAP and the Plant List datasets, a quantitative assessment of the distribution of criticality levels is performed. This assessment involves employing a combination of VLOOKUP and IF functions to count the number of assets falling into each criticality category (A, B, C, D, E) within each dataset. This analysis provides a clear understanding of the frequency and distribution of criticality levels for the assets in each dataset. As shown in Figure 13, for plant Z, the formulation of the criteria in column E are conducted. Where they are aimed at identifying the key metric in this analysis: **% of Mismatched Assets**. For the selected Plant Z, a significant 27% of assets present to be mismatched, which is considered a poor performing plant.

5. **Summarization of Findings:** The final step involves summarizing the findings to explore the level of agreement in criticality assessments between the SAP and Plant List datasets. As in the previous steps, every plant is evaluated individually. The selected Plant Z has its own results. This step aims to summarize the findings of Plant Z to gain a more detailed view of the overall situation.

As shown in Figure 14 below, a summary for every plant (rows), that encompasses every metric(columns) data has been conducted. Most of the findings are beyond the scope of this project, but includes other valuable data that I sought to be valuable to management at Company X. In the scope of this project, I was given permission to share the relevant metric: % Matching Criticalities. The findings are: Only 63% of assets contain criticalities that are matched in both SAP and the Plant List.

Confidential

Plant Name	Plant #	Total in SAP	Total in Crticality	Difference in # of Assets	% Difference in # of Assets	% Matching Criticalties	# of MISmatched Crticalities	% Assets-No criticality in SAP	ABC Count in SAP	ABC count in Ranking	% Difference
New Nlm	8302										
Beaver Dam	8305										
Springfield	8311										
Champaign	8318										
Lowville	8322										
Coshocton	8325										
Jacksonville Cof	8329										
Columbia	8330										
Kirksville	8333										
Newberry	8335										
Woodstock	8337										
Winschester	8342										
Fresno	8343										
Garland	8346										
Granite	8354										
Massillon	8355										
Avon	8356										
Fremont	8357										
Mason City	8360										
Muscatine	8362										
Mt Royal	8366										
Jacksonville	8367										
Cedar Rapids	8370										
Mason	8373										
Fort Myres	8374										
Dover	8376										
Kendallville	8378										
San Diego	8383										
Escallon	8384										
Holland	8385										
Irvine	8390										
Davenport	8394	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
		Average	3041,03	697,13	21.2%	Total:	43092				

Figure 14: Summary of Data Analysis

4.2.2 Physical Audit

After conducting the data analysis to identify the asset criticality data mismatch between SAP and the Plant List, an essential step in the resolution process is to conduct a physical check. This step aims to ensure complete verification and validation of each asset's criticality, leaving no room for inaccuracies or discrepancies in the data.

To implement this physical check, the methodology is communicated to the plant manager, who plays a crucial role in overseeing the accuracy of asset data within their respective facilities. Armed with the methodology and clear guidelines, the plant manager takes on the responsibility of physically inspecting each asset to confirm its correct criticality level.

During the physical check, the plant manager collaborates with maintenance personnel and relevant stakeholders to cross-reference the existing data with the actual status of each asset on-site. The process involves meticulous scrutiny of asset labels, tags, or identifiers, along with detailed inspections of asset functionalities, operational significance, and criticality.

By updating the Plant List asset data through this physical verification process, Company X achieves a significant milestone in building a reliable and accurate decision-making data set. The accurate asset criticality information empowers the maintenance department and other stakeholders to make well-informed decisions, prioritize maintenance activities effectively, and allocate resources optimally.

The physical check not only addresses the immediate issue of asset criticality data mismatch but also lays the groundwork for ongoing data integrity. It establishes a robust validation process that helps maintain the accuracy of asset data over time. As a result, the organization can avoid potential pitfalls caused by outdated data, minimizing risks and improving overall maintenance performance.

Moreover, this process fosters a culture of data-driven decision-making and accountability within Company X. The involvement of plant managers and maintenance personnel in the physical verification fosters a sense of ownership over asset data accuracy, encouraging a proactive approach towards data management and quality assurance. The physical check serves as a crucial step in resolving the asset criticality data mismatch between SAP and the Plant List.

4.3 Results

The data analysis section of this research involved conducting the same analysis outlined above on the post-physical check data set for Plant Z. Through effective cooperation with the plant manager and following the methodology detailed in this research, the results have proven to be highly promising.

The implementation of the three-way data check, combining software and physical verification, yielded a significant **23%** increase in asset criticality match for Plant Z. Prior to the analysis, the plant experienced a considerable mismatch in asset criticality data, hindering the effectiveness of maintenance decisions and resulting in operational inefficiencies.

However, after the successful application of the methodology, the plant's overall mismatch reduced to an impressive **4%.** As a result, Plant Z can now be categorized as a well-performing plant, with a remarkable **96%** of assets correctly criticalized across all data sets. This significant improvement in data alignment ensures that decisions regarding maintenance activities are based on more accurate and reliable information, allowing the plant to optimize its operations and allocate resources more efficiently.

The positive outcomes of this data analysis have the potential to serve as a motivational example for the remaining 31 plants within Company X. By showcasing the benefits of accurate asset data, Plant Z can inspire other plants to adopt similar methodologies and improve their own asset criticality match rates. The ripple effect of this improvement may lead to a company-wide transformation, where data-driven maintenance strategies become the norm, fostering a culture of continuous improvement and enhanced performance across all plants.

5.0 Application: Future preventative measures

While solving the current mismatch of asset data is a crucial step towards addressing the immediate issue, it is imperative to recognize that a long-term solution requires preventative measures to ensure the non-recurrence of this problem in the future. This chapter focuses on investigating how Company X can prevent the reoccurrence of unreliable asset data. The research question tackled in this chapter, question 4, encompasses the development of a tool to prevent future data entry errors for new assets and the implementation of data control and management practices to monitor data quality within the organization.

In this chapter, the research question below will be tackled in two steps. Step one: identifying the solution. The solution of creating a standardized process flowchart for the incoming asset process has been formulated using discussions with the selected research expert, team members, and the head of global maintenance. The solution was not hard to brainstorm as the need to fil the gap that was identified in the problem cluster in chapter 1 intuitively allowed us to identify the need for one. Step two: to further validate the effectiveness of applying the flowchart, the method of literature review will be conducted in this chapter to validate our solution before application.

4 - How can Company X prevent the reoccurrence of un-reliable asset data?
What method can be applied to prevent future incoming assets from being falsely data filled?
How can Company X ensure the quality and consistency of these data attributes through proper data collection methods and data management practices?

The chapter begins by introducing a process flowchart tool that would enable stakeholders to deal with new assets in a standardized manner, thereby eliminating the possibility of human data entry errors. Currently, Company X lacks a standardized process for handling new assets, highlighting the need for the introduction of this tool to improve data accuracy and consistency.

Furthermore, the chapter addresses the importance of implementing data control and management practices. These practices are essential for ensuring the quality and reliability of data attributes by establishing protocols for data collection, validation, and maintenance. By incorporating these practices, Company X can effectively monitor data quality and mitigate the risks associated with unreliable asset data.

The findings presented in this chapter are formulated through expert opinions, a comprehensive literature review, and internal observations. By drawing upon these sources, valuable insights and best practices can be identified to guide the implementation of preventative measures and enhance data quality control within Company X. Overall, this chapter aims to provide practical solutions and recommendations for preventing the reoccurrence of unreliable asset data, fostering a sustainable and efficient data management framework.

5.1 Incoming Asset tool

In addition to the challenges posed by poor data quality of existing assets, it is crucial to examine how newly acquired assets are handled in terms of data management within Company X. Understanding the data treatment process for new assets is essential to comprehensively address the issue of poor data quality.

This highlights another critical problem that Company X faces: the absence of a standardized system or process flow to guide employees when dealing with new assets. The lack of a structured approach leaves room for human errors and inconsistencies in data entry, contributing to the poor data quality observed in the organization. Without clear guidelines or a defined process, employees may interpret asset data differently, leading to misclassification and inaccuracies in asset records.

The absence of a standardized system for handling new assets creates a significant challenge for data management within Company X. It introduces variability in how asset data is captured, stored, and updated, which ultimately impacts the quality and reliability of the data. Inconsistent data entry practices can lead to discrepancies in criticality assignments, incomplete asset information, or data duplication, further exacerbating the issues surrounding data quality.

To address this problem effectively, it becomes crucial for Company X to establish a standardized system or process flow for employees to follow when dealing with new assets. Such a system should provide clear instructions on data entry, asset classification criteria, and validation processes. By implementing a standardized approach, the company can minimize human errors, ensure data consistency and accuracy, and enhance the overall quality of asset information.

The introduction of a standardized system or process flow would bring numerous benefits to Company X. Firstly, it would reduce the likelihood of misclassification errors, ensuring that new assets are assigned the correct criticality level from the outset. This would improve the accuracy of asset records and enable more precise decision-making based on reliable data.

Furthermore, a standardized system would streamline data entry and update processes, reducing the risk of incomplete or duplicate data. This would enhance the overall integrity and completeness of asset information, making it easier for employees to access and utilize the data effectively.

Additionally, by providing clear guidelines and training for employees on data management practices, the standardized system would foster a culture of data accuracy and responsibility. This would empower employees to take ownership of data quality and ensure adherence to standardized processes, contributing to improved overall data governance within the organization.

In conclusion, the absence of a standardized system or process flow for handling new assets represents a core problem within Company X, leading to poor data quality and misclassification errors. Establishing a standardized system would address this issue, reducing human errors, improving data consistency and accuracy, and enhancing overall data quality. By implementing such a system, Company X can ensure that new assets are managed consistently and accurately from the outset, laying the foundation for reliable and high-quality asset data throughout their lifecycle.

What tool can be constructed and applied to prevent future new assets from being falsely data filled?

As Company X is lacking any kind of standardized process to follow for incoming assets, the formulation of a simple decision-making process flowchart for a production plant to use when dealing with incoming assets is a good idea and an effective way to prevent future false or incomplete asset data as it will leave little to no room for human errors. The use of a flowchart would provide a standardized, systematic approach to human decision-making, making sure that all relevant factors are considered and followed in a standardized manner.

The following are academic literature sources that were found to validate the effectiveness of the chosen solution:

Realyvásquez-Vargas et al. (2018) goes on to discuss the user-friendly interface of flowcharts. The paper mentions that a flowchart uses visual symbols such as boxes, ovals, diamonds, and arrows to represent the steps and decisions in a process, which provide a clear identification of the processes happening for the user. The authors argue that a flowchart provides a clear and concise representation of the decision-making process, making it easier for individuals to understand and follow. A flowchart would ensure all necessary steps are conducted and none missed. In the context of asset management in Company X, a flowchart can be particularly beneficial in preventing false or incomplete asset data.

Polenghi et al. (2019) highlights the importance of effective asset management decision-making, particularly in the manufacturing sector. The research identifies information management as a key risk source that can influence the achievement of asset management objectives. By using a flowchart, the decision-making process can be structured and standardized, reducing the risk of missing or inaccurate information.

Furthermore, McMahon et al. (2020) emphasizes the importance of utilizing big data technologies for asset condition information management in improving asset management decision-making. The enormous quantity of data gathered from assets may be analyzed and interpreted with the use of a flowchart. It may make sure that the relevant data is taken into account and incorporated into the decision-making process, resulting in decisions that are more precise and well-informed.

Conducting a physical verification of assets offers a host of valuable benefits, primarily by ensuring data consistency and dependability between different data sources. This process becomes instrumental in enhancing decision-making for the management team at Company X. With accurate and synchronized asset data, they can make well-informed strategic choices concerning resource allocation, maintenance priorities, and investment planning. The resulting data-driven decision-making process not only improves operational efficiency but also reduces the risk of basing critical decisions on inaccurate or incomplete information.

Beyond management, maintenance personnel and technicians directly engaged in asset management stand to gain significantly from this approach. By ensuring data consistency, they can confidently rely on the information provided in the datasets to plan and execute maintenance tasks with precision. Consequently, improved asset reliability, minimized downtime, and optimized maintenance schedules are realized, leading to cost savings and heightened productivity throughout the organization.

The financial department of the plant also benefits from this comprehensive asset verification. Reliable asset information allows for more accurate budgeting and financial forecasting, enabling the organization to allocate resources wisely and optimize overall plant performance. This improved financial planning fosters stability and better prepares the company for unforeseen challenges and opportunities.

This endeavor enhances collaboration and communication between different departments within Company X. When various teams have access to synchronized and reliable asset data, it fosters better coordination and understanding among teams, leading to a more efficient and harmonious workflow across the organization. This improved interdepartmental cooperation paves the way for streamlined processes and better overall performance.

Furthermore, external stakeholders, including auditors and regulatory bodies, also benefit from this approach. Accurate and dependable asset data ensures compliance with industry standards and regulatory requirements. It strengthens the company's position during audits and ensures transparency in reporting, which is crucial for maintaining trust and credibility among external partners and stakeholders.

5.2 Results

The current situation at Company X involves handling new assets without a standardized process, resulting in complexities, errors, and data discrepancies. The lack of a well-defined system hampers the organization's ability to efficiently integrate incoming assets, leading to potential risks and operational inefficiencies. The Incoming Asset Flowchart Tool represents a significant contribution to addressing the existing challenges.The superiority of the Incoming Asset Flowchart Tool lies in its ability to streamline asset integration, reduce errors, and enhance data accuracy. Unlike the previous ad-hoc approach, this standardized process leaves no room for ambiguity, ensuring consistent and reliable results. By adopting this systematic approach, Company X can expect improved operational efficiency, reduced costs, and enhanced decision-making capabilities.

More importantly, as the company aims to transition to a more efficient data-driven maintenance strategy, the adoption of this asset flowchart tool becomes paramount. It ensures that the company establishes a reliable data baseline, enabling consistent and confident data-based decision-making without questioning the integrity of the data. With this standardized process in place, stakeholders can now fully trust the data sources before them, enabling them to make informed decisions with utmost confidence. Gone are the days of uncertainty and hesitancy; the asset flowchart provides a clear and reliable path to follow, empowering Company X to embrace a data-driven approach with conviction and assurance.

The process begins with the arrival of a new asset. The first step is to determine whether it is a replacement or non-replacement asset. A replacement asset is intended to provide the newest version or replace an existing worn-out asset with the same technical specifications. A non-replacement asset on the other hand, is a new asset strategically selected to offer an intended improvement or growth for the operating line: a new asset with upgraded specifications.

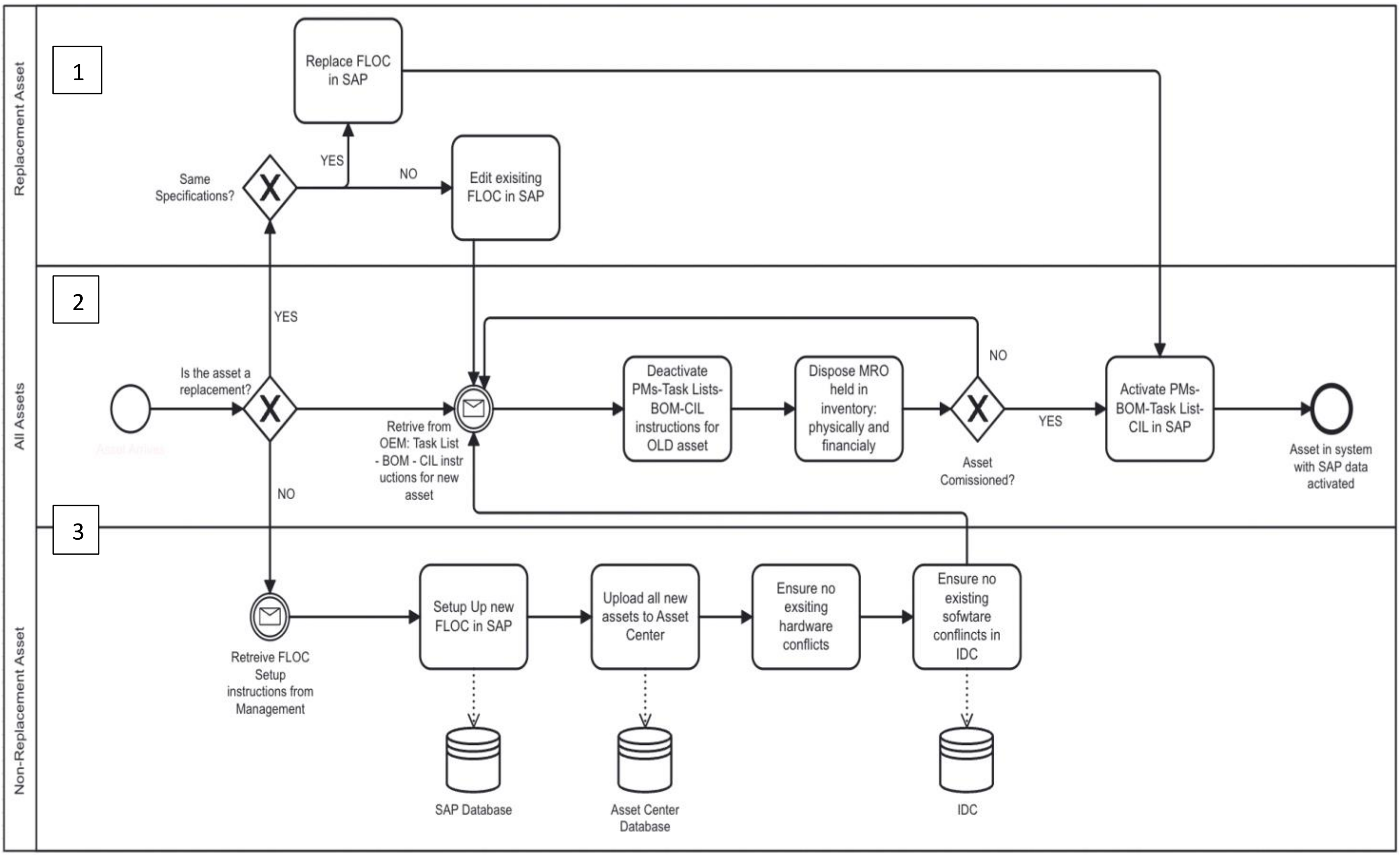


Figure 15: Incoming Asset Flowchart Tool

If an asset is determined a replacement asset (see 1 in figure 15), the asset goes through the gateway: *does the new asset possess the same specifications as the asset to be replaced?* These specifications provide essential information about the asset, such as its size, capacity, functionality, performance capabilities, materials used in construction, and any specific features or configurations. Additionally, asset specifications play a crucial role in determining the asset's criticality and maintenance requirements, supporting the organization in optimizing maintenance strategies and overall operational performance. If the asset does have the same specifications, it goes to the activity flow: *Replace FLOC in SAP* (see table below). If not, the asset goes to the activity flow: *Edit existing FLOC in SAP* (see table below).

	Updating the existing functional location of assets in the SAP system when new assets with identical specifications are received. It ensures that the accurate identification of assets is maintained within the database. By replacing the asset's functional location, or the FLOC, the system can keep track of the assets' latest status, location, and maintenance requirements, enabling effective management and allocation of resources.
	When new assets with upgraded specifications are received, this activity involves modifying the existing functional location of the assets in the SAP system to reflect their improved features accurately. This step ensures that the SAP database remains up-to-date with the most recent asset information, enabling accurate decision-making and resource allocation based on the assets' capabilities.

Table 2: Replacement Assets Activities

On the other hand, the process of introducing non-replacement assets (3 in figure 15) starts with an incoming information gathering message flow, where the user receives detailed FLOC instructions from management. This ensures that the asset is accurately identified and allocated within the asset management system. After the required instructions have been received, the asset smoothly navigates through the processes in the table below.

	This activity involves creating a new functional location (FLOC) in the SAP system for the newly arrived asset. The new FLOC ensures that the asset is accurately identified and managed within the system, providing a unique identifier for easy tracking and referencing.
	This step involves uploading all information related to the new assets into the asset center database. This centralized database serves as a comprehensive repository of asset information, enabling efficient asset tracking, management, and decision-making across the organization.
	This activity aims to make sure of the hardware compatibility of the asset to the intended production line.
	This step aims to verify and eliminate any existing software conflicts in the Integrated Data Center (IDC). Ensuring a smooth integration of the new asset within the IDC environment helps maintain data accuracy and consistency across the organization's systems.

Table 3: Non-Replacement Assets Activities

Finally, both replacement and non-replacement assets eventually converge into the "All Assets" process (see 2 in Figure 15). Here, the process is divided by first the user making sure all specifications and instructions are gathered for the asset, then the flow goes on to dispose of the old asset and activate the new one.

First, the user goes through the message flow of acquiring detailed maintenance instructions and relevant data from the Original Equipment Manufacturer (OEM) for the new assets. These instructions include task lists, bill of materials, and clean inspection lubrication (CIL) guidelines, which are essential for effective maintenance planning and execution. The user now commences the process of deactivating the old asset through the two activity processes in the table below.

Deactivate PMs-Task Lists-BOM-CIL instructions for OLD asset	When a new asset is introduced to replace an existing one, this activity involves deactivating all maintenance-related instructions associated with the old asset. This is essential to ensure that there are no overlapping or conflicting maintenance instructions, preventing confusion and maintaining data accuracy during the transition.
Dispose MRO held in inventory: physically and financialy	This activity involves physically and financially disposing of the Maintenance, Repair, and Operations (MRO) items that were associated with the old asset. Proper disposal ensures that the inventory reflects the actual stock of MRO items, minimizing discrepancies and unnecessary costs.

Table 4: All Assets Activities

Missing this step can result in bigger implications to data quality and hinder data-driven decision. If a disposed asset is still activated in the system, it may still go through automated maintenance instructions which may result in the unneeded allocation of labor and resources.

The culmination of the Incoming Asset Flowchart Tool lies at the decision gateway of asset commissioning. This phase ensures that the new asset is thoroughly tested to verify its compliance and functionality according to design specifications and operational requirements.

If the asset successfully passes the commissioning test, the outlined maintenance instructions are activated in SAP, and the asset is integrated into the system, fully operational with all required maintenance procedures in place. Which would be concluded with the step below.

Activate PMs-BOM-Task List-CIL in SAP	Once the new asset is appropriately set up and validated, this step involves activating the maintenance instructions, bill of materials (BOM), clean inspection lubrication (CIL) instructions, and task list in the SAP system. This ensures that the new asset is fully integrated into the maintenance processes and that all necessary instructions are readily available for effective maintenance activities.

Table 5: Final Activity : Asset Activation

However, if the asset fails the commissioning test or exhibits discrepancies, the process flow is sent back to the first message flow of part 2 in Figure 15. The asset is then carefully reviewed, and revisions are made to the OEM specifications so the process flow can operate smoothly. This iterative approach ensures that any identified issues are addressed before proceeding with the final activation of the asset’s maintenance instructions.

In summary, the Incoming Asset Flowchart Tool serves as a cornerstone in the seamless integration of new assets within Company X. This standardized process offers a structured approach that brings about a shift in asset management practices for Company X. By adhering diligently to this flowchart, stakeholders ensure a reliable data set existing for any incoming asset, allowing them to comfortably take decisions accordingly. Stakeholders may now automate their asset maintenance tasks and purchases for incoming assets, using trusted data.

As Company X evolves towards its vision of a data-driven future, the Incoming Asset Flowchart Tool emerges as the beacon guiding them on this transformative journey. Its significance lies not only in the streamlining of asset integration but also in the profound impact it has on the entire organizational ecosystem. From enhancing maintenance performance to driving organizational success, this tool stands as a testament to Company X's commitment to excellence and innovation in the realm of asset management and maintenance practices.

6.0 Expected Benefits

After we were successful with the formulated asset data management tools, we reach an important stage of our research journey in this chapter. This chapter is an important step in making sure the solution was not just a situational success, but a long-lasting success. This idea would be explored in this chapter by first examining the future consistency of the proposed solution, then tackling sub-research question number 5 to explore expected cost reduction variables of the applied solution. Then this chapter concludes by answering sub-research question number 6, exploring the transition towards a data-driven maintenance policy.

6.1 Future Data Monitoring

In the context of Company X's asset management and the applied solutions of asset data, ensuring the quality and consistency of data attributes is of paramount importance for the improvements to be consistent in the future.

To address this concern, our research aims to explore effective data collection methods and data management practices that can guarantee the quality and consistency of these data attributes. By filling this gap in knowledge, our findings will offer valuable insights for Company X and other stakeholders in the industry, enabling them to enhance asset management practices, improve decision-making processes, and ultimately achieve higher levels of operational excellence.
To fill this knowledge gap, a comprehensive set of points were extracted using the literature review method outlined earlier, and the findings are the following methods:

- **Standardized Data Collection:** Implement standardized data collection procedures and templates to ensure consistency and accuracy across different sources. Establish guidelines for data entry, including defined data fields, formats, and validation rules. (Wilkinson et al, 2016)
- **Automation and Sensor Technologies:** Utilize automation and sensor technologies to capture real-time equipment performance data directly from the assets. This reduces manual data entry errors and provides more accurate and timely information. (Stoyanovich et al, 2020)
- **Data Validation and Verification:** Implement validation checks during data collection to ensure the quality and consistency of the collected data. This includes checks for data completeness, accuracy, and integrity. (Wilkinson et al, 2016)
- **Regular Data Audits:** Conduct regular audits of the collected data to identify and rectify any inconsistencies, outliers, or data anomalies. This helps maintain data quality and reliability over time. (Stoyanovich et al, 2020)
- **Data Governance and Stewardship:** Establish a data governance framework that includes clear roles and responsibilities for data stewardship. Assign dedicated data stewards who are responsible for data quality, data validation, and maintaining data standards. (Breunig et al, 2020)
- **Integration and Data Management Systems:** Utilize integrated data management systems, such as Computerized Maintenance Management Systems (CMMS) or Enterprise Asset Management (EAM) systems, to centralize and manage the collected data. These systems provide data validation, data storage, and data analytics capabilities. (Stoyanovich et al, 2020)

By collecting and maintaining these specific data attributes and implementing proper data collection methods and management practices, Company X can ensure the availability of high-quality, consistent data necessary to support a data-driven maintenance strategy. This enables the identification of maintenance patterns, prediction of failures, and optimization of maintenance activities for improved operational efficiency and cost-effectiveness.

6.2 Expected Costs Reduction Variables

Using the support of empirical evidence and academic literature, this section considers the expected operational and financial future benefits of this research. The following sub-research question is used to guide the search for the findings in this section:

How can the improvement of data quality contribute to reducing maintenance costs, minimizing equipment downtime, and optimizing resource allocation at Company X?

Improving the asset data quality of a production plant can have several benefits for Company X, including reducing maintenance costs, minimizing equipment downtime, and optimizing resource allocation. By ensuring accurate and reliable asset data, Company X can make informed decisions regarding maintenance activities, leading to cost savings and increased operational efficiency.

Empirical evidence supporting the statement can be found in research studies that have investigated the impact of improving asset data quality on production plants' performance and operational outcomes. One such study is conducted by Khan et al. (2017), where they examined the relationship between asset data quality and maintenance performance in a manufacturing plant.
Khan et al. (2017) conducted a case study in a production plant and analyzed the effects of improving asset data quality on maintenance costs, equipment downtime, and resource allocation. They implemented data quality improvement measures, including data cleansing, validation, and standardization, to ensure accurate and reliable asset data. The results of their study showed significant improvements in various aspects:

1. **Reduced Maintenance Costs:** By having accurate and reliable asset data, the maintenance team could proactively identify potential issues and schedule maintenance activities more efficiently. This preventive maintenance approach resulted in a reduction in unscheduled downtime and breakdowns, leading to cost savings in repair and replacement expenses.

2. **Minimized Equipment Downtime:** The improved asset data quality allowed for better asset tracking and monitoring, enabling early detection of equipment performance degradation or impending failures. As a result, the production plant experienced reduced downtime due to unplanned maintenance or unexpected breakdowns, leading to increased overall equipment availability and productivity.

3. **Optimized Resource Allocation:** With precise asset data, Company X could better allocate resources for maintenance tasks. The maintenance team could focus on critical assets or those exhibiting signs of potential issues, optimizing labor and spare parts usage. This efficient resource allocation led to improved maintenance effectiveness and cost-effectiveness.
Overall, the empirical evidence from Khan et al.'s (2017) study supports the idea that improving asset data quality can have several benefits for Company X, including reduced maintenance costs, minimized equipment downtime, and optimized resource allocation. Accurate and reliable asset data enables the organization to make informed decisions regarding maintenance activities, resulting in cost savings and increased operational efficiency in the production plant

In addition to cost savings, improving asset data quality can also minimize equipment downtime. Ineffective maintenance strategies can lead to unplanned downtime and decreased productivity (Mourtzis et al., 2023). By having accurate and reliable asset data, Company X can implement effective maintenance strategies, such as predictive maintenance, which can help identify potential equipment failures before they occur. This proactive approach to maintenance can significantly reduce equipment downtime and improve the overall reliability and availability of the assets.

Furthermore, optimizing resource allocation is another benefit of improving asset data quality. Company X would be more efficient to allocate resources, such as labor and materials, to the assets that need maintenance or repair if precise and complete asset data have been gathered. This can aid in maximizing resource utilization and ensuring that they are distributed effectively to reduce downtime and increase production. The adoption of a decision support system based on mathematical optimization can assist in maximizing production while fulfilling limits imposed by the assets and the production process, according to Teixeira et al. (2013). By using resources more effectively, Company X may see a drop in operating expenses.

Additionally, enhancing asset data quality can help Company X perform better overall and remain competitive. Company X may increase production efficiency and operating cost-effectiveness by lowering maintenance costs, minimizing equipment downtime, and optimizing resource allocation (Teixeira et al., 2013). This may result in more production, higher-quality products, and higher customer satisfaction. Additionally, Company X may improve its production processes and decrease downtime through real-time monitoring and predictive maintenance by implementing cutting-edge technologies like the Industrial Internet of Things (IIoT) and big data analytics (Peinado-Asensi, 2023). This implementation of advanced technologies will lead to more proactive and data-driven decision-making, enabling Company X to detect potential equipment issues in real-time, schedule maintenance activities more efficiently, and ultimately enhance overall production efficiency and equipment reliability.

The key takeaway from improving asset data quality is that it can lead to cost savings, minimized equipment downtime, and optimized resource allocation for Company X. This improvement is crucial for various stakeholders, including maintenance teams, production managers, and decision-makers within the company.

For maintenance teams, accurate and reliable asset data enables the implementation of effective maintenance strategies, such as predictive maintenance. By identifying potential equipment failures before they occur, maintenance teams can significantly reduce equipment downtime and enhance overall asset reliability and availability. This proactive approach to maintenance helps maximize equipment uptime and productivity.

Production managers benefit from improved asset data quality by being able to allocate resources more efficiently. With precise and complete asset data, they can allocate labor and materials to the assets that require maintenance or repair, ensuring that resources are distributed effectively to reduce downtime and increase production. The adoption of decision support systems based on mathematical optimization further aids in maximizing production while meeting asset and production process limits.

6.3 Complementing the transition from a budget-based to a data-driven maintenance strategy.

This section concludes the outlined sub-research questions of this research, by answering sub-research question number 6 below, this section explores how this proposed research would complement the Company's goals of transitioning towards a data-driven maintenance policy.

How can the improvement of data quality contribute to the transition from budget-based maintenance to data-driven maintenance?

The most significant advantage of this research for Company X is the increase of data quality, which is essential in enabling the shift from a budget-based maintenance approach to a more data-driven maintenance strategy inside Company X. The organisation may stop exclusively depending on financial concerns and start making decisions based on data-driven insights by improving the quality, completeness, and consistency of asset data.

One way data quality improvement contributes to this transition is by enabling predictive maintenance practices. Accurate and reliable asset data allows for the identification of patterns, trends, and anomalies that can help predict potential equipment failures or maintenance needs. This empowers Company X to implement proactive maintenance strategies, scheduling maintenance activities based on data-driven insights rather than predetermined budgetary allocations. As a result, maintenance efforts can be targeted more effectively, minimizing both planned and unplanned downtime and optimizing the utilization of resources.

Improved data quality supports condition-based maintenance approaches. With accurate and consistent asset data, Company X can monitor the condition and performance of its assets in real-time or through periodic inspections. This information allows for the customization of maintenance tasks to the actual state of each asset, optimising resource allocation and cutting down on pointless maintenance tasks. With the shift towards condition-based maintenance, resources may be used more effectively, which lowers the costs of both over- and under-maintenance situations.

Reliable asset data also enables more informed asset lifecycle management decisions. Accurate and reliable data provide insights into asset reliability, performance trends, and potential risks. With this information, Company X can make data-driven decisions regarding asset upgrades, replacements, or retirements, optimizing the allocation of financial resources and extending the lifespan of critical assets.

Overall, by improving data quality, Company X can transition from a budget-based maintenance approach to a more data-driven strategy. This transition allows for more proactive and efficient maintenance practices, leading to cost savings, improved asset performance, and increased operational reliability. The utilization of high-quality data as a foundation for decision-making fosters a culture of continuous improvement, driving the organization towards optimal maintenance strategies and improved overall business outcomes.

The references below provide more insights into the benefits and challenges of implementing data-driven maintenance strategies.

According to the reference "Future Maintenance and Service Innovation Using Industrial Big Data Analytics in The United States" (2023), businesses may use data-driven decision-making to boost equipment dependability, save maintenance costs, and increase operational efficiency. To overcome these difficulties, organisations must invest in the appropriate tools and technology as well as be aware of the difficulties that come with implementing a data-driven process strategy.

Merkt (2019) emphasizes that the data-driven perspective is now the preferred approach for improving maintenance quality in industrial environments. By utilizing machine learning techniques and sensor technology, organizations can analyze data to gain insights into the condition of production equipment and implement proactive maintenance strategies. This shift towards data-driven maintenance can lead to improved maintenance quality and adherence to industry standards.

Gopalakrishnan et al. (2020) emphasizes the significance of data-driven decision-making in maintenance and the demand for ongoing data quality improvement. Good data quality can significantly enhance the size and scope of improvements in companies. Therefore, organizations should start using data-driven decision-making to push for higher data quality.

Krupitzer (2020) emphasizes that a conventional, static maintenance schedule is outdated in the context of Industry 4.0 and Industrial IoT. The paper suggests that a proactive, data-driven maintenance strategy is ideal for achieving operational efficiency and reducing costs. However, this strategy requires high-quality and sufficient training data. The paper also discusses the use of data-driven techniques, such as deep learning models, for predictive maintenance in cyber-physical production systems. Organizations may predict possible equipment breakdowns and take preventive action by analyzing data to expose underlying patterns and enable proactive decision-making

One can conclude that enhancing data quality is necessary for the switch from budget-based to data-driven maintenance. Organizations may adopt preventive maintenance initiatives, increase operational efficiency, and save costs by assuring accurate and trustworthy data. To overcome these obstacles, organizations must invest in the appropriate tools and technology and be aware of the issues related to data-driven maintenance. For data-driven maintenance plans to be successful, data quality must constantly be improved (Merkt, 2019; Bampoula et al., 2021; Gopalakrishnan et al., 2020; Krupitzer, 2020).

7.0 Conclusion and Recommendations

In conclusion, this research has addressed the critical problem of poor data quality in Company X's asset management, particularly focusing on the mismatch of asset criticality data between SAP and the plant list. The significance of accurate asset data cannot be overstated, as it serves as the foundation for informed decision-making, proactive maintenance strategies, and efficient resource allocation.

To tackle the existing data mismatch a comprehensive method of fixing the current asset mismatch summarized in the figure below, was formulated using various methods and successfully applied. The results demonstrated a notable **23%** improvement in asset criticality match between the two data sources in the pilot plant selected for this research. This improvement in data accuracy directly contributes to better decision-making, reducing unnecessary costs associated with incorrect criticality assignments and optimizing maintenance activities.

Figure 16: Fixing current mismatch summary

To prevent the reoccurrence of the issue in the future, the implementation of a standardized Incoming Asset Flowchart Tool ensures a consistent and error-free process for handling new assets. By providing clear guidance for stakeholders, this tool prevents the recurrence of data quality issues related to misclassified assets. Moreover, it facilitates data monitoring practices to continually assess data reliability and validity, ensuring that the organization maintains a high level of data accuracy.

The combination of these solutions brings transformative benefits to Company X. Not only will they experience cost savings from avoiding unnecessary maintenance activities and excess inventory procurement, but also witness improved operational efficiency. Accurate and reliable data will enable better predictive maintenance, minimizing equipment downtime and extending asset lifespans. This shift from a budget-based maintenance strategy to a data-driven approach empowers the organization to make proactive decisions, optimizing maintenance efforts based on data insights.

Furthermore, the research outcomes have broader implications beyond Company X. The methodologies and tools developed here can be adapted and applied to other organizations facing similar data quality challenges in asset management. By adopting standardized processes and implementing data monitoring practices, these organizations can enhance their maintenance operations, reduce costs, and transition to data-driven strategies for improved asset performance and overall operational excellence.

In conclusion, the solution to the problem of poor data quality lies in meticulous data validation, standardized processes, and continuous data monitoring. These initiatives enable organizations to make more informed decisions, optimize resources, and drive their maintenance strategies forward with data as a reliable compass. By embracing these approaches, companies can navigate the challenges of asset management and unlock the full potential of their assets, positioning themselves for sustainable success in an increasingly data-centric world.

7.1 Recommendations

With respect to the outlined findings, the recommendations to enhance asset data quality and improve overall efficiency at Company X include the following key points:

1. **The Process Flowchart as a Standardized Tool**: The Process Flowchart introduced in Figure 15 serves as a crucial asset management tool for Company X. Its implementation ensures a standardized and foolproof approach for any plant employee when handling incoming assets. By following the step-by-step guidance provided in the flowchart, employees can confidently and accurately deploy new assets into the system, leaving no room for human data entry errors. The flowchart acts as a practical reference point, streamlining asset registration, functional location setup, and data entry processes. By utilizing this standardized tool, Company X can improve the accuracy and consistency of asset data right from the initial stages, setting a strong foundation for reliable asset information throughout its lifecycle.

2. **Matching Assets Methodology for Future Mismatches**: Despite the successful resolution of the existing data mismatch, it is prudent for Company X to be prepared for future instances of mismatched asset data. The Matching Assets Methodology outlined in Section 5.1 provides an effective approach to address such discrepancies. By employing a mixed method of VLOOKUP and IF functions, Company X can swiftly identify and rectify any future instances of misclassified assets between SAP and the plant list. Regular application of this methodology as part of routine data validation practices will enable the organization to maintain accurate and aligned asset criticality data. By proactively addressing future mismatches, Company X can ensure data consistency and reliability for optimal decision-making and maintenance planning.

3. **Data Governance Policies for Reliable Asset Data**: To sustain the quality of asset data in the long run, Company X should establish robust data governance policies, as outlined in Section 7.1. These policies lay the foundation for efficient data management, ensuring data accuracy, consistency, and security. By defining roles and responsibilities, data ownership, and data quality standards, Company X can foster a culture of data accountability across the organization. Implementing data governance policies involves regular audits and checks to enforce compliance and identify potential data quality issues promptly. Through a comprehensive data governance framework, Company X can uphold reliable asset data as a key organizational asset, supporting data-driven decision-making and proactive maintenance strategies.

4. **Empowering Employees for Reliable Asset Data**: In addition to implementing data management methodologies and policies, Company X should prioritize stressing the significance of asset data to its employees. By raising awareness about the direct impact of accurate and reliable data on maintenance operations and organizational success, employees will be motivated to uphold data quality. Training sessions, workshops, and communication campaigns can educate employees on the far-reaching consequences of data inaccuracies, instilling a sense of ownership and responsibility. By fostering a culture of data consciousness and recognizing employees' contributions to data integrity, Company X can create a workforce that actively strives for reliable asset data. Empowering employees in this manner will drive proactive measures to prevent errors and inconsistencies, resulting in a positive feedback loop of continual data improvement.

5. **Embrace Predictive Maintenance Technologies**: Building on the foundation of data-driven maintenance strategies, Company X should consider embracing predictive maintenance technologies. Exploring the integration of advanced analytics and artificial intelligence tools can unlock new opportunities for proactive maintenance, enabling the organization to predict and

prevent equipment failures before they occur. Integrating predictive maintenance technologies into the existing data-driven approach will further optimize maintenance schedules, reduce downtime, and enhance asset performance.

By integrating the Process Flowchart, the Matching Assets Methodology, and data governance policies into its asset management practices, Company X can solidify its commitment to accurate and reliable asset data by integrating the Process Flowchart, the Matching Assets Methodology, and data governance policies into its asset management practices, Company X can solidify its commitment to accurate and reliable asset data. These tools and policies work in synergy to ensure that asset criticality remains consistent, data mismatches are swiftly addressed, and data integrity is upheld throughout the asset lifecycle. The combined usage of these solutions will lead to cost savings, improved operational efficiency, and enhanced asset performance.

With the Process Flowchart, employees are guided by standardized procedures and decision-making gateways when handling new asset data, minimizing human errors and ensuring uniformity in data entry. The Matching Assets Methodology facilitates the comparison of data from different sources, identifying discrepancies, and allowing for timely data updates. By implementing data governance policies, Company X establishes a framework for data quality management, ensuring ongoing data accuracy, consistency, and compliance with industry standards.

Embracing data-driven maintenance practices, supported by reliable asset data, will ultimately position Company X as a leader in the industry. Real-time monitoring and predictive maintenance, fueled by high-quality asset data, enable proactive decision-making and timely maintenance interventions. This positions Company X to adapt to changing demands and challenges efficiently, while maximizing the value of its assets and ensuring optimal performance throughout their lifecycle. As a result, Company X can achieve a competitive advantage, foster continuous improvement, and solidify its position as a leading player in the market.

These tools and policies work in synergy to ensure that asset criticality remains consistent, data mismatches are swiftly addressed, and data integrity is upheld throughout the asset lifecycle. The combined usage of these solutions will lead to cost savings, improved operational efficiency, and enhanced asset performance. Embracing data-driven maintenance practices and maintaining reliable asset data will ultimately position Company X as a leader in the industry, equipped to adapt to changing demands and challenges while maximizing the value of its assets.

7.2 Future Research Recommendations

Future research within Company X holds significant potential for further enhancing asset management and maintenance practices. The study focused on addressing the core problem of poor data quality and implementing solutions for accurate asset criticality data. Several avenues for future investigations can build upon these efforts and optimize maintenance operations even further.

One promising area for future research is to delve deeper into the impact of the implemented data monitoring practices on maintenance performance over an extended period. A longitudinal study could assess the sustained benefits of the Incoming Asset Flowchart Tool and the three-way data check methodology, providing valuable insights into their long-term effectiveness in maintaining data accuracy and preventing data quality issues.

Moreover, investigating the correlation between improved data quality and key maintenance performance indicators can shed light on the direct impact of accurate data on maintenance costs, equipment downtime, and resource allocation. Statistical analyses can quantify the extent to which data-driven maintenance strategies contribute to tangible cost savings and operational efficiencies. By comparing maintenance costs, equipment downtime, and resource allocation before and after implementing data-driven strategies, organizations can determine the actual cost savings achieved and improvements in operational efficiency.

To perform this analysis, organizations must ensure they have a well-structured data collection system that captures relevant asset information accurately and consistently. Implementing advanced data analytics tools and machine learning algorithms can help process and interpret vast amounts of data efficiently, enabling organizations to identify patterns, anomalies, and predictive maintenance opportunities. With accurate and reliable data, organizations can proactively identify potential maintenance issues and prioritize maintenance activities based on asset condition, leading to more efficient resource allocation.

By evaluating the correlation between data quality and maintenance performance indicators, organizations can make data-driven decisions to optimize maintenance strategies, allocate resources effectively, and enhance overall operational efficiency. This approach reduces reactive maintenance costs and minimizes equipment downtime. Insights gained from data analysis enable organizations to continuously improve data quality practices and embrace a culture of data-driven decision-making, fostering a cycle of continuous improvement.

Future research additionally could explore the adoption of predictive maintenance technologies, leveraging advanced analytics, artificial intelligence, and machine learning algorithms. Predictive maintenance optimizes maintenance schedules, identifies potential equipment failures proactively, and streamlines maintenance activities. Assessing the feasibility and benefits of implementing predictive maintenance tools can enhance asset performance and extend equipment lifespans. Investigating the integration of maintenance data with other organizational data streams, such as production data and supply chain information, can provide a more holistic understanding of asset performance and its impact on overall business operations. This comprehensive approach to data analysis offers valuable insights into the interplay between maintenance activities and organizational performance, supporting informed decision-making at a strategic level.

Future research within Company X is critical to advancing asset management practices and driving efficiencies across industries. The findings will contribute to the growing body of knowledge in asset management and maintenance, shaping a future of productivity and sustainability.

References

Wilkinson, M. D., Dumontier, M., Aalbersberg, I. J., Appleton, G., Axton, M., Baak, A., ... Martone, M. (2016). The FAIR Guiding Principles for scientific data management and stewardship. Scientific Data, 3.

Stoyanovich, J., Howe, B., & Jagadish, H. V. (2020). Responsible data management. Proceedings of the VLDB Endowment, 13, 3474-3488.

Breunig, M., Bradley, P. E., Jahn, M. W., Kuper, P. V., Mazroob, N., Rösch, N., ... Jadidi, M. (2020). Geospatial Data Management Research: Progress and Future Directions. ISPRS International Journal of Geo-Information, 9, 95.

Rasiel, E. M., & Friga, P. N. (2001). The McKinsey mind: Understanding and implementing the problem-solving tools and management techniques of the world's top strategic consulting firm. McGraw-Hill.

Agusthiyar, A. (2014). A Simplified Framework for Data Cleaning and Information Retrieval in Multiple Data Source Problems. International Journal of Innovative Research in Science, Engineering, and Technology, 03, 15401-15407.

Tee Wooi Keat, Mohamad Wijayanuddin Ali, Harisun Ya'akob. (2019). Strategic Asset Management Maintenance Framework in Asset Reliability Management for the Oleochemical Industry in Malaysia. AJTVE, 1(3). https://doi.org/10.26666/rmp.ajtve.2019.1.2

Mourtzis, D., Tsoubou, S., & Angelopoulos, J. (2023). Robotic Cell Reliability Optimization Based On Digital Twin and Predictive Maintenance. Electronics, 9(12), 1999. https://doi.org/10.3390/electronics12091999

Patidar, S. (2019). Preventive Maintenance and Essential Optimizations: A Review. IJEAST, 2(4), 182-185. https://doi.org/10.33564/ijeast.2019.v04i02.033

Peinado-Asensi, I. (2023). Industrial Internet Of Things and Big Data Techniques For The Smart Press Shop 4.0 Development In The Automotive Industry. IOP Conference Series: Materials Science and Engineering, 1(1284), 012012. https://doi.org/10.1088/1757-899x/1284/1/012012

Teixeira, A., Campos, M., Barreto, F., Stender, A., & Arraes, F. (2013). Model-Based Production Optimization Applied To Offshore Fields. https://doi.org/10.4043/24301-ms

Heerkens, H., & Winden, A. V. (2017). Solving managerial problems systematically. London: Routledge.

Blumberg, B., Cooper, D. R., & Schindler, P. S. (2014). Business research methods. London: McGraw-Hill Education.

Price, P. (2015). Reliability and Validity of Measurement. In Research methods in psychology, 2nd Canadian edition. essay, BCcampus.

Tentale, E. A. (2009). Optimum preventative maintenance strategies using genetic algorithms and Bayesian updating. DOI: 10.1080. Retrieved from www.webofscience.com

Makelarski, J., et al. (2013). Are Your Asset Data as Good as You Think? Conducting a Comprehensive Census of Built Assets to Improve Urban Population Health. Retrieved from www.webofscience.com

Hadian, M. (2023). Development of a simulation-based optimization approach to integrate the decisions of maintenance planning and safety stock determination in deteriorating manufacturing systems. Retrieved from www.sciencedirect.com

Patidar, S. (2019). Optimization of preventive maintenance in manufacturing. International Journal of Industrial Engineering Computations, 10(4), 683-700.

Mourtzis, D., Fotia, S., & Vlachou, E. (2023). Improving maintenance strategies for increased productivity. Journal of Manufacturing Systems, 58, 179-196.

Teixeira, J. C. M., Barbosa-Póvoa, A. P., & Novais, A. Q. (2013). Optimization models for production planning in manufacturing: A critical review. European Journal of Operational Research, 227(3), 353-371.

Peinado-Asensi, J. (2023). The impact of the Industrial Internet of Things and big data analytics on manufacturing. Procedia CIRP, 63, 655-660

Appendix A: Asset Criticality

What is asset criticality?
Asset criticality refers to the level of significance or importance assigned to different assets within a manufacturing company. It involves assessing and categorizing assets based on their potential impact on operations, productivity, and overall business performance. By understanding asset criticality, a manufacturing company can prioritize its resources, investments, and maintenance activities accordingly. Assets with higher criticality require more attention, monitoring, and preventive maintenance to ensure their optimal performance and minimize the risk of downtime or disruptions that could negatively impact production efficiency, quality, and customer satisfaction. Ultimately, asset criticality plays a vital role in facilitating strategic decision-making, resource allocation, and maintenance planning within a manufacturing organization.

How is asset criticality determined?
Company X has a standardized process in determining asset criticality: there exists an interactive excel tool that collects input from the user and calculates the asset criticality. As seen in the Figures below, there exists four factors that are used to determine an asset's criticality, where each factor is judged based on its severity and probability. Each asset receives a numerical score for its severity and probability for each possible event. Where the excel tool formulates a criticality score for each factor of the 4. Finally, the tool then takes the average of these 4 criticalities to pinpoint an overall criticality score (A-E). All factors share the same probability scale, scaling from "Not Likely" to "Nearly Certain". However, each factor has different levels of severity, which will be discussed below.

<u>Factor One: Safety</u>

Safety Criticality Matrix

Probability	Severity				
	Potential Loss of Life	Loss of Body Part	Other Recordable	First Aid	Near Miss
Nearly Certain	A	A	B	C	C
Highly Likely	A	B	B	C	C
Likely	B	B	C	C	D
Low Likelihood	C	C	C	C	D
Not Likely	C	C	D	D	E

Severity	
Potential Loss of Life	Accidents with risk of death.
Loss of Body Part	Accidents with loss of body parts.
Other Recordable	Other recordable accidents such as loss of flesh, broken bones, cuts or burns.
First Aid	Minor abrasions or bruises. any injury that is treated with one of the 14 treatments listed in OSHA's 1904.7(b)(5)(ii) standard.
Near Miss	Incident with no consequences. An unplanned event caused by an unsafe act or condition that did not result in consequence (injury, illness or damage).
Probability	
Nearly Certain	Nearly Certain is when singular event(s) has a high (weekly) frequency over the past period.
Highly Likely	Highly Likely is when random unrelated events has a high (weekly) frequency over the past period.
Likely	Likely is when singular events has a low (monthly) frequency over the past period.
Low Likelihood	Low Likelihood is when random unrelated events has a low (monthly) frequency over the past period.
Not Likely	Not Likely is when random unrelated events has a very low (annually) frequency over the past period.

Figure 17: Safety Criticality Matrix

This is the most important factor, as safety is the number one priority of any manufacturing plant. Intuitively, the severity of this factor investigates the potential physical harm on the blue-collar employees of the plant. More details and the criticality assessment can be seen in Figure 17.

Factor two: Environment

Environmental Criticality Matrix

Probability	Severity	Receptor is will be Impacted	Receptor could be impacted	Receptor may be impacted but not likely	Receptor unlikely to impacted	Receptor no impacted
	Nearly Certain	A	A	B	C	C
	Highly Likely	A	B	B	C	C
	Likely	B	B	C	C	D
	Low Likelihood	C	C	C	C	D
	Not Likely	C	C	D	D	E

Severity	
Example Receptors	- People -Domestic and commercial property -Infrastructure -Ecosystems -Animals -Plants -Controlled waters
Probability	
Nearly Certain	Nearly Certain is when singular event(s) has a high (weekly) frequency over the past period.
Highly Likely	Highly Likely is when random unrelated events has a high (weekly) frequency over the past period.
Likely	Likely is when singular events has a low (monthly) frequency over the past period.
Low Likelihood	Low Likelihood is when random unrelated events has a low (monthly) frequency over the past period.
Not Likely	Not Likely is when random unrelated events has a very low (annually) frequency over the past period.

Figure 18: Environmental Criticality Matrix

This is a factor that is increasing in popularity among the manufacturing industry lately due to increased attention and care towards our environment. This factor looks at the level of impact to the environment, which encompasses ecosystems, people, plants, animals, and more in Figure 18.

Factor 3: Quality

Quality Criticality Matrix

Probability	Severity	High Severity	Medium Severity	Low Severity	No Physical Illness/ Harm	Minimal to No Impact
	Nearly Certain	A	A	B	C	C
	Highly Likely	A	B	B	C	C
	Likely	B	B	C	C	D
	Low Likelihood	C	C	C	C	D
	Not Likely	C	C	D	D	E

Severity	
Highly Severe	A food safety or product quality condition that could result in a trade withdrawal, product recall, legal violation or potential loss of life.
Potential Loss of Life	Evidence indicating that a product / finished goods have been manufactured with potential food safety or product quality implications that could result in a trade withdrawal, product recall legal violation or potential loss of life.
Medium Severity	Evidence that an existing procedure / process is not being followed or is ineffective and could result in a food safety or product quality incident, severe illness or legal violation.
Low Severity	Evidence that an existing procedure / process is not being followed or is ineffective but unlikely to result in a food safety or product quality incident or legal violation or potential minor illness.
No Physical Illness or Harm	Evidence that an improvement could be made by implementing good practice. No physical illness or harm is apparent. Evidence that a single step in an existing procedure / process is not being followed or is ineffective.
Minimal to No Impact	This is the default value and should be selected if there are no priority actions or recommendations. There is no quality impact or harm.
Probability	
Nearly Certain	Nearly Certain is when singular event(s) has a high (weekly) frequency over the past period.
Highly Likely	Highly Likely is when random unrelated events has a high (weekly) frequency over the past period.
Likely	Likely is when singular events has a low (monthly) frequency over the past period.
Low Likelihood	Low Likelihood is when random unrelated events has a low (monthly) frequency over the past period.
Not Likely	Not Likely is when random unrelated events has a very low (annually) frequency over the past period.

Figure 19: Quality Criticality Matrix

This factor investigates the impact an asset has (in the occurrence of failure) towards the quality of the products produced. As Company X operates in the food and beverage industry, the quality of the products must always be attained at the highest level, and there is no to little room for errors.

Factor 4: Production

Production Criticality Matrix

Probability	Severity: Unacceptable, no alternatives exist	Major reductions, no workaround available	Moderate reductions, workaround available	Moderate impact, can continue as is	Minimal to No Impact
Nearly Certain	A	A	B	C	C
Highly Likely	A	B	B	C	C
Likely	B	B	C	C	D
Low Likelihood	C	C	C	C	D
Not Likely	C	C	D	D	E

Severity	
Unacceptable, no alternatives exist	This would be an event that is a day or greater of no production for a line of area. Also would impact other lines or areas.
Major reductions, no workaround available	This would be an event that is a shift or greater, but less than a day of limited production for a line of area. Also may impact other lines or areas.
Moderate reductions, workaround available	This would be an event that is a four hours or greater, but less than a shift of no production for a line of area. Also may impact other lines or areas.
Moderate impact, can continue as is	This would be an event that would affect the throughput for the shift or day of reduced production for a line of area. May not impact other lines or areas. Should not affect other lines or areas.
Minimal to No Impact	This would be an event that would have little effect on the throughput for the shift or day. Should not affect other lines or areas.
Probability	
Nearly Certain	Nearly Certain is when singular event(s) has a high (weekly) frequency over the past period.
Highly Likely	Highly Likely is when random unrelated events has a high (weekly) frequency over the past period.
Likely	Likely is when singular events has a low (monthly) frequency over the past period.
Low Likelihood	Low Likelihood is when random unrelated events has a low (monthly) frequency over the past period.
Not Likely	Not Likely is when random unrelated events has a very low (annually) frequency over the past period.

Figure 20: Production Criticality Matrix

Factor 4 investigates the affect an asset failure has on the production performance of the plant. An asset failure can range from unsignificant production line slowdowns all the way to stopping the production line to failure, and in some cases affecting other production lines.

Appendix B: Background Knowledge of Budget-Based and Data-Driven Maintenance Strategies

Budget-Based Maintenance Strategy: Budget-based maintenance is a traditional approach to maintenance management where decisions regarding maintenance activities are primarily driven by financial considerations. In this strategy, maintenance budgets are allocated based on predetermined financial plans and limitations. Maintenance activities, such as repairs and replacements, are often conducted reactively in response to equipment failures or based on fixed time intervals.

Under the budget-based maintenance strategy, asset criticality may not be thoroughly considered, and resources may be allocated based on generic guidelines or historical spending patterns. Decisions are often made on a cost-reduction basis, aiming to meet financial targets while prioritizing immediate budget constraints. This strategy relies on predefined budgets and may lead to a reactive maintenance approach, where maintenance is carried out only when necessary or affordable within the allocated budget.

Data-Driven Maintenance Strategy: On the other hand, a data-driven maintenance plan emphasises the use of data and analytics to inform maintenance management decision-making. It uses cutting-edge technology to gather and analyse current or past data on asset performance, health, and maintenance needs. These technologies include predictive analytics, machine learning, and condition monitoring systems.

Data-driven maintenance aims to proactively manage assets based on their actual condition, predicted failure patterns, and business priorities. It involves utilizing algorithms and data models to identify potential equipment failures, determining optimal maintenance schedules, and deploying resources efficiently. By incorporating data-driven insights into maintenance planning, organizations can optimize asset performance, reduce downtime, and enhance overall operational efficiency.

Key Differences: The differences between budget-based and data-driven maintenance strategies are notable. Budget-based maintenance relies on predefined budgets and reactive decision-making, often resulting in higher equipment downtime, increased maintenance costs, and suboptimal resource allocation. Maintenance activities are typically performed based on fixed time intervals or as a reaction to failures, without considering real-time asset condition or potential failure patterns.

In contrast, data-driven maintenance strategies utilize advanced data analytics, real-time monitoring, and predictive modeling to optimize maintenance planning and resource allocation. This approach allows for proactive maintenance interventions, reduced downtime, improved asset performance, and optimized resource utilization. Data-driven maintenance prioritizes asset health, criticality, and condition information, enabling organizations to make informed decisions based on data insights rather than solely financial considerations.

By transitioning from a budget-based to a data-driven maintenance strategy, organizations like Company X can benefit from improved maintenance outcomes, reduced costs, and enhanced operational efficiency. The data-driven approach allows organizations to shift from reactive practices to proactive asset management, leveraging data to optimize maintenance activities, allocate resources effectively, and finally extend asset lifespan.
Understanding the differences between these two maintenance strategies is essential for organizations seeking to improve their maintenance practices and maximize asset performance. By embracing data-driven approaches, companies can unlock the potential of advanced analytics and optimize maintenance strategies based on accurate and timely information.

Appendix C: BPMN Notations

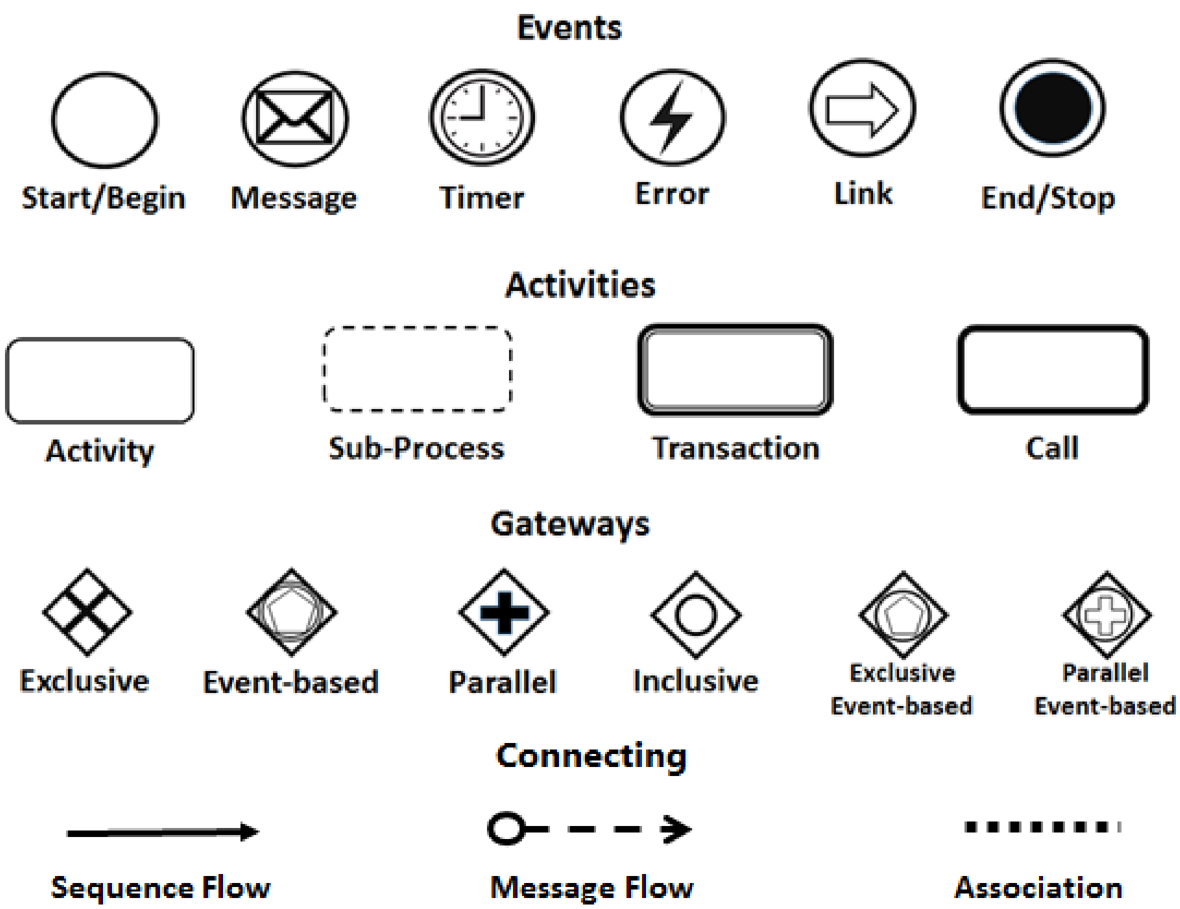


Figure 21: BPMN Notations