University of Stavanger

Faculty of Science and Technology

MASTER'S THESIS

Study program/ Specialization: The Spring Semester, 2023

Industrial Asset Management

Open access

Author:

MAJID FOUAD AHMED SHALFAWI

Majid F.A Shalfawi

Author's signature

Faculty Supervisor(s):

Ali Turlyilmaz / Idriss El-Thalji

Thesis title:

Modelling of Maintenance Service Workshop and Inventory Operations for a Short Cycle Operational Region.

Credits (ECTS):
30

Key Words:

- Inventory Management
- Short-cycle operations
- Repair-path cycle
- Maintenance workshop
- Enhanced model

Pages: 103

Stavanger, June 24, 2023

Abstract

The North Sea region sees a high operational cycle of tools that require frequent maintenance check-ups, repairs, and preparations for subsequent operations. Given the quick-paced nature of these operations, the availability of spare parts at the maintenance workshop is critical for maintaining minimal flow time. Adding to the challenge is the practice of sourcing spare parts from best-cost countries, leading to a lead time of approximately one year, thus necessitating an optimal economic order quantity and reorder point. The balancing act between maintaining sufficient inventory at the workshop and managing operational expenses through batch ordering of spare parts is a complex one. Frequent supply requirements contribute to the environmental impacts through increased spare part scrap rates. With these challenges in mind, this thesis aims to develop a simulation model capable of quantifying the costs and benefits associated with reusing repaired spares, as compared to procuring newly built spares from best-cost countries. To achieve this, a case study focusing on a specific maintenance workshop within the North Sea region was carried out. The comprehensive tool repair and spare part supply operations were conceptualized and modeled using a simulation approach. Two operational scenarios were simulated: the first, where the maintenance workshop was completely dependent on newly built spares sourced from best-cost countries, with no inventory stock dedicated for spares re-usage. In the second scenario, the workshop primarily relied on repaired spares, with a safety level of new build stock maintained. The results, guided by the research question probing the impact of implementing a repair-path cycle process within the maintenance process, showed that the enhanced model significantly outperformed the baseline model across several key metrics over a model time run of three years. These include a 78% reduction in lead times, a 116% improvement in worker utilization, a 73% reduction in crowding levels, a 52% reduction in scrap rate, and a potential profit increase of roughly three million NOK (20%). This thesis provides evidence that the enhanced model, with its focus on repaired spares, presents a more sustainable, efficient, and profitable solution to the challenges of inventory management in high-cycle operations. It is important to note, however, that the sensitivity of these results is closely tied to the high procurement lead times.

Acknowledgments

I would like to express my gratitude to every single person who supported me throughout the research and writing of this thesis on inventory management.

First and foremost, I am extremely thankful to my thesis advisors, Idriss El-Thalji and Ali Türkyilmaz, for their invaluable guidance, encouragement, and insightful feedback throughout the process. Their knowledge and dedication have been instrumental in shaping the direction and scope of this work, and I have learned a great deal from their mentor ship.

I am also grateful to the faculty members and colleagues in the Industrial Asset Management program for their support and constructive comments on my research. Their diverse perspectives and critical insights have challenged me to think more deeply about the subject matter and have greatly contributed to the quality of this thesis.

I would like to extend my appreciation to the organizations and individuals who have generously shared their time, data, and resources with me during the research phase of this thesis. Their contributions have been crucial in providing me with the empirical evidence and case studies necessary to support my arguments.

Finally, I would like to thank my family and friends for their unwavering support and encouragement throughout this journey. Their love, understanding, and patience have been instrumental in helping me to stay focused and motivated during the challenging moments.

To all those who have contributed in some way to this thesis, I offer my sincere thanks and gratitude.

Majid F.A Shalfawi

June 24, 2023

Contents

List of Figures

List of Tables

Chapter 1

Introduction

This chapter will provide an overall background on the topic's relevance in the industrial world and give more context about oil & gas spare parts inventory management. A project plan will be presented within the final section of this chapter.

1.1 Background, Relevance & Motivation

Effective inventory management is a critical aspect of any supply chain, particularly in the oil and gas sector where procurement issues may arise due to geographical challenges. Previous researches have extensively explored various inventory policies aimed at optimizing spare part management, these policies can be generally categorized into continuous and periodic review strategies [1].

Koçağa and Şen explored the intricacies of spare part inventory management where demand lead times and rationing are essential factors. They consider the (T, Q) policy, which is a periodic review policy with a fixed replenishment order size. While this strategy offers a certain level of consistency, it may lack the flexibility required to promptly address variations in demand. Their study identifies strategies for optimally setting rationing levels and reordering points to improve system performance [2].

Li, Zhang, and Tan delve into spare part management within a testing workshop setting. They employ a simulation model to study the impact of different inventory policies on system performance. Their work emphasizes the need for inventory control policies that are responsive to specific contexts, including both the nature of demand and supply considerations [3].

A different approach to inventory management is seen with the (s, Q) policy, a continuous review strategy that replenishes spare parts when the stock level reaches certain reorder points. Miranda et al. developed a mixed-integer, nonlinear programming model based on the (s, Q) policy that considers both inventory control and facility location [4]. While continuous review policies may result in higher inspection costs, they also provide greater flexibility in responding to demand fluctuations.

In the context of the oil and gas industry, Ali et al. proposed an improved Maintenance, Repair, and Overhaul (MRO) inventory management system. They highlighted the importance of considering the full life-cycle of spare parts, from initial procurement to eventual disposal. Their proposed system resulted in an increased service level and reduced average inventory investment, suggesting that a holistic approach to MRO inventory management can yield substantial benefits [5].

A similar perspective is offered by Saeed & Mojahid, who developed a model and simulation for inventory management of repairable items in maintenance systems. This approach not only accounts for the potential reuse of repairable items but also provides a robust method for handling uncertainties associated with the repair process. His findings underline the importance of a repair path cycle in maintenance systems and the potential cost and time savings that can be realized through its implementation [6].

Finally, integrating demand forecasting into inventory management has been proven to be beneficial. Van der Auweraer and Boute presented a methodology to forecast spare part demand using service maintenance information. Accurate demand forecasting can help to reduce stockouts and excessive inventory, contributing to more efficient inventory management [7].

All the mentioned studies focused on various inventory control policies and logistical lead time challenges; however, they had no considerations to integrate repair policies in order to handled the obstacles faced by a short-cycle region. A short-cycle region is a region of high operational cycle of tools that require frequent maintenance check-ups, repairs, and preparations for subsequent operations.

1.2 Research Needs & Gaps

As it stands, there is a distinct need for studies that focus on integrating inventory control policies, and repair policies, under short cycle operational demands with high logistical lead time challenges to enable managers to comprehensively manage the entire spare part supply chain. Strategies like Turan et al.'s risk-averse simulation-based approach, which jointly optimizes workforce capacity, spare part stocks, and scheduling priorities, show potential. However, additional research is necessary to develop an inventory policy that addresses the unique challenges of the oil and gas sector, such as geographical constraints and the need for swift offshore operations [8].

The challenges described here are what the case company of this research is dealing with, so the proposed enhancement to the maintenance process flow structure through a repair path cycle is a promising avenue that needs further exploration.

The inclusion of the repair path cycle in inventory management for industries like oil and gas where equipment is expensive and can often be repaired rather than replaced, can help reduce costs, improve resource utilization, and reduce waste.

This would be done in this research by including simulation modeling which is a effective tool for examining complex inventory systems, allowing decision-makers to test different strategies and policies without disrupting real-world operations. It can provide insights into system behavior and performance under various scenarios, enabling the design of more efficient and effective inventory management system [3].

All in all, a more integrated, demand-responsive, and lifecycle-aware approach to spare part inventory management seems to be the direction towards a more efficient and effective system. Therefore, further research is needed to develop an inventory policy that takes into account the unique challenges within the oil and gas sector.

Applying theoretical frameworks like Queuing Theory, Economic Order Quantity (EOQ) Model, ABC Analysis, data analytics, and simulation modeling assists in creating a more responsive and cost-effective inventory management system. The proposed enhancement to the maintenance process flow structure through a repair path cycle holds potential for reducing maintenance delays and improving the speed of offshore operations.

1.3 Case Company

This research revolves around the maintenance workshop of a classified for confidentiality reasons company that will be referred to as "Company A" throughout. The workshop operates on a fleet of tools that are rented out to offshore operations. This creates a revenue stream for the case company.

The case company has been facing elongated lead times due to repair delays and stock shortages. This created a challenge on meeting operational demands especially since they operate as a short cycle region with quick turnarounds as low as two weeks at a time from the moment the tool is back loaded onshore till the offshore shipping date. The confidentiality of the case company extends to the tool naming all throughout the research. All maintenance processes and data gathered came directly from interviews with a tool specialist at the company, along with the maintenance historical data provided by them.

1.4 Research question and Objectives

The primary aim of this research is dual in a sense, where firstly, it aims to explore the implications of introducing a repair-path cycle into the established maintenance process flow within the case company. This objective is driven by the need to assess whether such an approach can enhance the effectiveness of the maintenance process, ultimately benefiting the overall operational performance of the company. Secondly, this study aims to design a practical, executable model of the repair-path cycle that specifically targets the reduction of lead times and the improvement of operational efficiency.

What is the effect of the repair-path cycle on the maintenance process flow implemented at the case company?

This question seeks to understand the potential effects and improvements that the introduction of a repair-path cycle might bring about within the current maintenance procedures of the company. This includes aspects such as process efficiency, resource allocation, and operational adaptability.

How can the repair-path cycle be modeled practically to illustrate the operational behavior in terms of lead times and operational efficiency?

This question aims to develop a pragmatical application of the repair-path cycle that not only theoretically promises improvements, but also delivers tangible benefits when implemented. This requires careful consideration of the unique operational characteristics and constraints of the case company when developing the simulation model, ensuring that the proposed model is not only effective but also feasible within the company's operational context.

1.5 Research limitations

In order to fulfill the aims and objectives of this research effectively within the given timeframe that starts in February 2023 and ends in June 2023, certain boundaries and delimitations were put in place to focus the scope of the study. These delimitations, while essential for practical reasons, do impose some constraints on the breadth and generalizability of the research.

The study is confined to a single tool from the fleet managed by the case company. By restricting the focus to one tool, the research can delve deeper into the specific operational intricacies associated with that particular piece of equipment. However, it should be noted that the findings may not necessarily apply to all tools within the fleet due to the variations in design, functionality, and maintenance requirements among different tools.

Furthermore, the research will concentrate on the five most critical components of the chosen tool. The determination of 'critical' was made based on the component's impact on overall tool functionality and availability along with its maintenance needs frequency. While this allows for a more focused study of the components that significantly influence the tool's operation and maintenance, it does limit the understanding of other less critical but potentially impactful components.

The supply chain aspect of the research has also been delimited. The research assumes a single supply vendor with a fixed supply delay time. This decision was made to control the number of variables within the study and provide a clearer view of the system. The assumption of a fixed supply delay time allowed for a focus on internal operational factors rather than external supply uncertainties, having taken a. However, in the real-world scenarios, supply times can vary due to numerous factors, and multiple vendors might be involved, adding complexity to the supply process. Therefore, the outcomes related to supply logistics should be understood within this context of simplification.

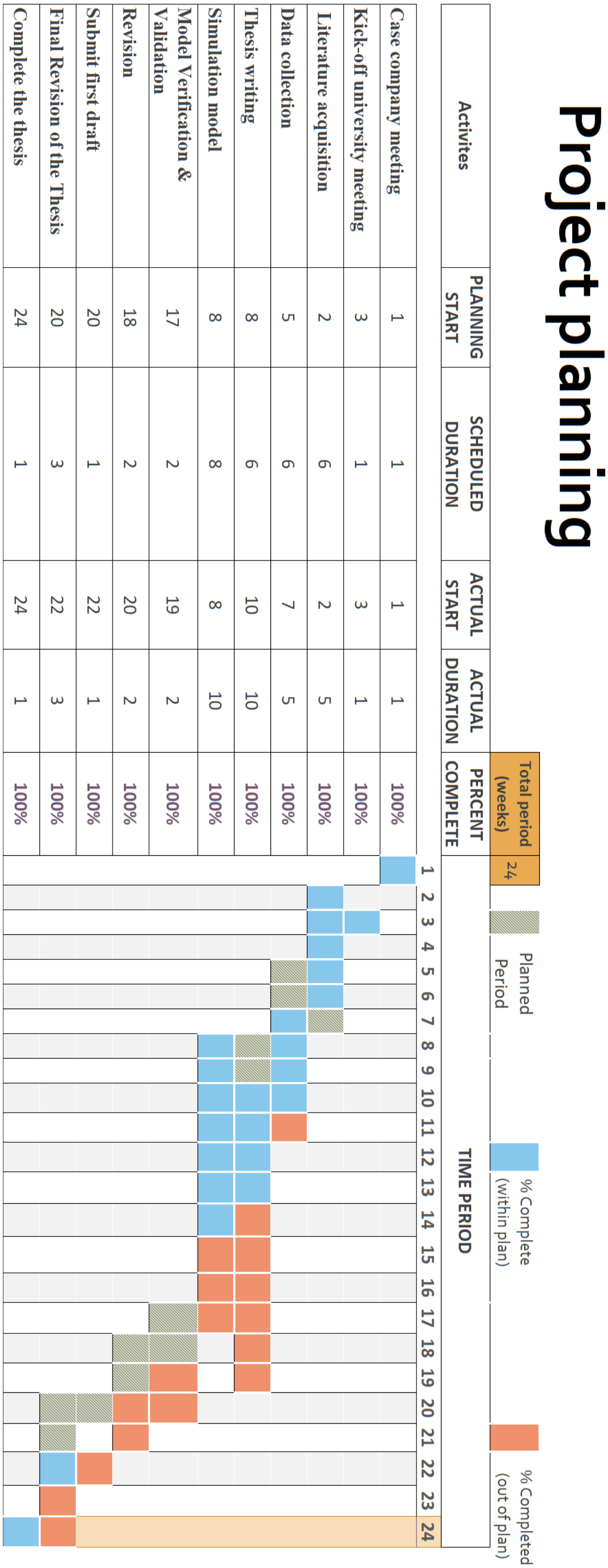
1.6 Project Planning

In order to successfully complete this research project within a single semester, a meticulous week-by-week plan has been designed. The completion deadline for this project in June 2023, and the plan broke down the distinct stages over the time period provided. This weekly plan provided a roadmap for the successful completion of the project within the timeframe. However, it's also important to note that flexibility was required to adapt to all unexpected changes or challenges during the research process.

The first four weeks involved establishing the research questions, developing the study's framework, and initiating the literature review process. The next four weeks were planned to be dedicated to data collection; however, the data collection was only achievable starting in week 7 due to unforeseen delays. This included liaising with "Company A" to access needed data, such as historical maintenance data, operational records, and information about the tool under study and its critical components.

The simulation model structure began regardless of the data collection delay and ended later than scheduled due to the unforeseen model complexities. Moreover, the thesis writing began two weeks later than scheduled and only ended in week 19. During this period, the model was thoroughly tested using different scenarios and refined based on the feedback from these tests.

Weeks 19 to 21 were dedicated to validating the model results from the model and discussing these findings in the context of the study's objectives and the reviewed literature. The project report will also be finalized during this period. Following that, initial drafting of the project report also began two weeks delayed and the thesis was submitted after reviews as planned. A better visualization of the plan is provided below in Figure 1.1.



Activites	PLANNING START	SCHEDULED DURATION	ACTUAL START	ACTUAL DURATION	PERCENT COMPLETE
Case company meeting	1	1	1	1	100%
Kick-off university meeting	3	1	3	1	100%
Literature acquisition	2	6	2	5	100%
Data collection	5	6	7	5	100%
Thesis writing	8	6	10	10	100%
Simulation model	8	8	8	10	100%
Model Verification & Validation	17	2	19	2	100%
Revision	18	2	20	2	100%
Submit first draft	20	1	22	1	100%
Final Revision of the Thesis	20	3	22	3	100%
Complete the thesis	24	1	24	1	100%

Figure 1.1: *Project plan.*

1.7 Research structure

The thesis structure following this chapter was divided below:

Chapter 2: Theories and Literature Review - This chapter will review existing literature on spare part inventory management, inventory control policies, repair policies, demand forecasting, and simulation. It will provide a theoretical foundation for the research.

Chapter 3: Research Methodology - This chapter will detail the research approach, data collection methods, and analysis techniques used in the study.

Chapter 4: Data Collection - This chapter details the methods of collecting the case company's data, alongside all parameters and national standards considered, while also censoring the data in a way that complies with the case company's privacy.

Chapter 5: Analysis - This chapter will detail the findings from the case study of Company A, including an analysis of the current inventory management practices and the application of the proposed inventory policies.

Chapter 6: Results and Discussion - This chapter will discuss the findings of the research in relation to the research objectives and questions. It will also discuss the implications of the findings for spare part inventory management in the oil and gas industry.

Chapter 7: Conclusion - This chapter will provide a summary of the research findings, limitations of the study, and recommendations for future research.

Chapter 2

Theories & Literature Review

This chapter will review existing theories and literature on spare part inventory management, inventory control policies, repair policies, national standards, demand forecasting, and simulation. It will provide a theoretical foundation for the research.

2.1 Spare Parts Inventory Management

Inventory management is an essential process in any industry. However, in the oil and gas industry, where equipment failure could lead to costly downtime and safety risks, efficient spare part inventory management is of great importance. Traditional theoretical approaches to inventory management include the Economic Order Quantity (EOQ) model, the Just-in-Time (JIT) model, and the ABC analysis.

2.1.1 Economic Order Quantity (EOQ) Model

The EOQ model, introduced by Harris in 1913, is a fundamental theory in inventory management. It attempts to determine the optimal order quantity that minimizes the total inventory cost, considering the cost of holding inventory, order cost, and shortage cost. However, its main limitation is its deterministic approach - it assumes a constant demand and lead time, which is rarely the case in the real world and particularly in the volatile oil and gas industry [9].

2.1.2 Just-in-Time (JIT) Model

The JIT model, emanating from the Toyota Production System, focuses on reducing inventory to the bare minimum. The idea is to order parts just when they are needed, reducing holding costs. JIT works well when suppliers are reliable and the lead times and demand are predictable. However, in the oil and gas industry, where equipment often operates in harsh conditions and the failure rates can be unpredictable, JIT could lead to increased risk of equipment downtime due to parts unavailability [10]

2.1.3 ABC Analysis

ABC Analysis is a method for classifying inventory items based on their importance. Class A items are the most valuable products, typically accounting for a significant portion of the company's total value but only a small portion of total quantity. Class B items are moderately valuable, while Class C items make up the majority of the quantity but contribute less to the total value. This method allows managers to focus their efforts on managing the items that have the greatest impact on the business's overall inventory cost [2]. It provides a structured approach but does not explicitly incorporate the specificities of the oil and gas sector such as high cost of downtime, varying criticality of parts, and erratic failure patterns [11].

2.1.4 Safety Stock in Streamlining Maintenance Processes

Safety stock is additional inventory held parts to mitigate the risk of stock-outs due to demand and lead time variability. In the oil and gas industry, maintaining an appropriate level of safety stock for critical spare parts can help streamline maintenance processes and minimize equipment downtime. By replacing a faulty component with a safety stock item, maintenance can be performed without waiting for the original component to be repaired and coated, thereby reducing maintenance time and costs.

To determine the optimal safety stock level, several factors should be considered. These include demand and lead time variability, where greater variability in demand and lead time requires higher safety stock levels to ensure an acceptable service level [12]. In the context of 'Company A', this variability is very prevalent when it comes to lead times due to the fact the components are shipped across continents, and therefore, maintaining the best cost country suppliers would require better inventory management processes and enhancements, and by extension, the presence of this research.

Moreover, service level requirements are to be considered, meaning that having higher service levels necessitate more safety stock to reduce the risk of stock-outs, and finally, the cost trade-offs, and these are the costs of carrying safety stock against the costs of stock-outs, such as lost production and equipment downtime, is essential for optimal safety stock determination [13].

Finally, integrating safety stock optimization with other inventory management techniques, such as demand forecasting, ABC analysis, and a stochastic model, develops a comprehensive approach to streamline maintenance processes and meet operational demands with minimal downtime and costs.

2.2 Replenishment policies

Spare part inventory management has been a topic of extensive research due to its significance in reducing machine downtime, optimizing resources, and minimizing costs. The literature reveals a wide range of replenishment and repair policies implemented by various industries, underlining the trade-off decisions that companies must take in managing their spare part inventories [7]. Two primary areas of focus can be deduced from the literature being inventory control policies and repair policies.

2.2.1 Inventory Control Policies

Inventory policies can be broadly classified along two dimensions, being review methods and order sizes. The literature delineates between continuous review policies and periodic review policies on the one hand, and between fixed quantity orders and variable quantity orders on the other [4].

Continuous review policies demand constant monitoring of inventory levels and trigger a reorder when a predetermined level, being the reorder point, is reached. Conversely, periodic review policies involve assessing inventory levels at fixed intervals and ordering accordingly. While continuous review policies offer high levels of responsiveness, they incur large inspection costs and administrative overheads [14].

Regarding order sizes, fixed quantity orders involve ordering a predetermined number of spare parts each time, while variable quantity orders flexibly adjust the order quantity based on the current demand and inventory status. While fixed quantity orders simplify the order process, they may fail to meet variable demand in the next period, leading to potential breakdown losses [15].

These stocking policies govern when and how much inventory should be replenished. Among these, the Reorder Point (ROP) policy and the Min-Max policy have been widely studied. ROP policy sets a predetermined inventory level at which a replenishment order is triggered. In contrast, the Min-Max policy requires a replenishment order when the inventory reaches the minimum threshold, bringing the stock back to the maximum level [8]. These strategies are often adopted in industries with high variability in demand or long lead times for obtaining spare parts [6].

2.2.2 Common Inventory Policies in Practice

Through combining some of the classification dimensions, several notable policies emerge: the (T, Q) policy, (T, S) policy, (s, S) policy, and (s, Q) policy. The (T, Q) policy implies a periodic review with a fixed replenishment order size. The (T, S) policy also involves periodic review but allows for variable order quantities. The (s, S) policy adopts continuous review with variable order quantities, while the (s, Q) policy follows a continuous review strategy with fixed order quantities [14].

2.2.3 Limitations and Opportunities in Inventory Policy Research

While these policies have proven effective in numerous scenarios, several studies have highlighted their limitations, particularly in settings with frequent and unpredictable changes in demand, such as short-cycle operation regions [3]. In these environments, traditional stocking policies may result in higher inventory carrying costs and increased risk of stockouts, necessitating more dynamic and flexible approaches.

Only a few studies have attempted to integrate inventory control with other crucial aspects of spare part supply chain management, such as supply coordination and demand forecasting. This lack of comprehensive approaches makes it difficult for managers to holistically manage the entire spare part supply chain and realize its full effectiveness.

2.2.4 A Focus on the (T, s, S) Policy

The present study aims to address this research gap by exploring the three-echelon spare part inventory and supply model under the (T, s, S) policy. This policy, which combines elements of periodic review and variable order quantities, offers a promising avenue for optimizing spare part inventory management in a holistic manner. Its potential benefits and drawbacks, as well as its applicability in different operational contexts, will be thoroughly examined.

The (T, s, S) policy is an inventory management strategy that has emerged from the literature as an effective mechanism for managing variable and uncertain demand [14]. The policy employs a combination of both periodic review and variable order quantity systems to optimally manage inventory levels.

Review Period (T): This component of the policy denotes the fixed intervals of time at which inventory levels are checked, as described in the work of [15]. The measurement of time 'T' could be in days, weeks, or months, depending upon the specific inventory context and operational requirements.

Reorder Point (s): If the inventory level falls below 's' units at the time of review, a replenishment order is triggered. This is consistent with the established principles of the reorder point system [4]. The specific value of 's' is typically determined by considering the forecasted demand and the desired service level, ensuring a balance between availability and overstocking.

Order-Up-To Level (S): The 'S' in the policy refers to the target inventory level post-replenishment. According to the work of Al-Rifai et al., the quantity ordered under this policy is variable, with the aim to bring the inventory level up to 'S' units. This level is usually set higher than 's' to avoid stock-outs, but is also carefully managed to avoid the costs of excessive inventory.

This policy, as examined within various studies by Al-Rifai et al., Miranda et al., and Tagaras et al. offers a way to navigate the trade-offs inherent in inventory management [4, 14, 15]. It achieves this by coordinating regular inventory reviews with variable replenishment quantities, geared towards a target inventory level, thus balancing the dual objectives of maintaining service levels and controlling inventory costs. Further studies are warranted to examine the effectiveness and applicability of this policy across different operational contexts.

2.3 Repair Policies

Repair policies, on the other hand, deal with the decision of whether to repair or replace defective spare parts. Three main strategies discussed in the literature include Repair and Stock (RS), Stock and Queue (SQ), and Stock and Serve (SS) [16]. RS strategy focuses on repairing or refurbishing spare parts as needed, while SQ has the spare parts stocked in inventory without repair or refurbishment and waiting to be repaired by an external supplier when it is needed.

2.3.1 Integration of policies Applied

Stock and Queue (SQ) policy focuses on storing spare parts in inventory without any prior repair or refurbishment. Upon demand, these spare parts are sent out for repair or refurbishment [7]. This policy primarily relies on external suppliers or repair centers to fulfill the repair requirements. The lead time for repair, which includes the time spent in queue for servicing, is an important factor under this policy. Despite potential challenges with lead times, the SQ policy could help in minimizing the need for extensive internal repair resources and can be beneficial when external repair services offer cost or quality advantages [8].

The (T, s, S) Policy: As previously discussed, this inventory management strategy involves regular checks of inventory levels at fixed intervals (T), triggering a replenishment order if the inventory falls below a certain level (s), and adjusting the order quantity to reach a set inventory level (S) [14, 15]. This policy provides a robust and flexible framework to balance customer service levels and inventory value cost limitations.

By integrating the SQ and (T, s, S) policies, the research tries to explore the potential synergies between outsourcing repair tasks to external suppliers and maintaining optimal inventory levels using a time-based policy. This approach aligns the advantage of reducing the need for substantial internal repair resources with a systematic method to ensure spare part availability. It not only contributes to the academic understanding of the interaction between these two policies but also provides valuable insights for practitioners seeking to improve spare part inventory management in maintenance service workshops, particularly in short-cycle operation regions as the case is with the case company issue at hand. This integrative approach, emphasizing both repair policy and inventory management, offers a novel perspective in the field of spare part inventory management research.

2.4 Demand Forecasting

Accurate demand forecasting is essential for effective spare parts inventory management in the oil and gas industry. Several forecasting techniques have been proposed in the literature: Time series analysis: Time series models, such as autoregressive integrated moving average (ARIMA) and exponential smoothing state space model (ETS), can capture patterns and trends in historical demand data [17, 18].

2.4.1 Intermittent Demand Forecasting in Inventory Management

Intermittent demand forecasting is a critical aspect of inventory management, particularly for industries where the demand for spare parts is irregular and sporadic, such as the oil and gas industry. Traditional time series forecasting methods, such as exponential smoothing and moving averages, are not suitable for intermittent demand due to the presence of zero or near-zero demands for a set of periods, that is then followed by irregular spikes in demand [19]. As a result, specialized intermittent demand forecasting methods have been developed to better predict the demand for spare parts in industries with irregular demand patterns.

Croston's method is one of the most widely used approaches for intermittent demand forecasting. It involves separately forecasting the demand size and the demand interval, then combining the two forecasts to estimate the expected demand per period. Croston's method has been demonstrated to be more accurate than traditional time series forecasting methods for intermittent demand situations [20].

Several variations of Croston's method have been proposed in the literature to address its shortcomings, such as the TSB (Teunter-Syntetos-Babai) method [21]. These methods aim to improve the accuracy and responsiveness of intermittent demand forecasting by considering factors such as demand intermittence, the bias in the estimation of demand size and interval, and the variability in the demand process.

Incorporating intermittent demand forecasting methods into the inventory optimization model can significantly enhance the accuracy of demand forecasts for tool maintenance, especially within the case company's short turnarounds. This, in turn, can lead to more effective inventory management and reduced maintenance lead times and costs. It incorporates two smoothing parameters, alpha for demand size and beta for demand interval [21].

It is a novel approach which incorporates distinct simple exponential smoothing techniques for estimating the probability of demand occurrence and the demand size separately. The estimate for the probability of occurrence is updated at regular time intervals, whereas the estimate for the demand size is only updated at the end of periods with positive demand. The forecast for demand per period is obtained by multiplying the estimates for demand size and demand probability. To ensure accurate predictions, two different smoothing constants are employed, with the demand probability being updated more frequently compared to the demand size. This approach overall allows for more precise and dynamic forecasting of intermittent demand.

2.4.2 Python for demand forecasting

As a programming language with comprehensive libraries and robust data handling capabilities, Python found increasing application in various forecasting techniques, including demand forecasting for inventory management. The ease of implementation, the ability to handle large data sets, and the availability of several packages for statistical analysis make Python a suitable tool for developing forecasting models [22].

Python's libraries, such as pandas for data manipulation and SciPy and NumPy for numerical computation, have found significant use in handling and processing inventory data for demand forecasting. More specifically, these libraries can be used for preparing and manipulating time series data, which forms the basis for intermittent demand forecasting [23].

For the implementation of intermittent demand forecasting methods, such as the TSB (Teunter-Syntetos-Babai) modification of Croston's method, Python can offer a flexible and efficient coding environment. With the TSB method's inherent complexity, particularly the separate consideration of demand occurrence probability and demand size using different exponential smoothing techniques, Python's ease of use in defining custom functions and algorithms makes it well-suited for such implementations.

In the context of TSB's modified version of Croston's method, Python can be utilized to develop a forecasting model by firstly setting up two distinct simple exponential smoothing methods, one for estimating demand size and the other for demand occurrence probability. This would involve using separate smoothing constants for each, with the demand probability updated more frequently. The final forecast for demand per period can be calculated by multiplying the estimated demand size and probability, which is a process that Python can easily handle through its numerical computation capabilities.

Further enhancements to these Python-based forecasting models could incorporate machine learning libraries such as scikit-learn or TensorFlow. These libraries can help in automating model tuning and provide options for advanced techniques such as neural networks for more accurate forecasting [24].

Therefore, Python, with its robust data handling and computation capabilities, is a powerful tool for demand forecasting. When applied to inventory management in the oil and gas industry, Python can provide precise, dynamic, and efficient demand forecasting models that can substantially contribute to reducing maintenance lead times and costs. It's also important to note that as open-source software, Python encourages sharing and collaboration, which may be of value for research and development teams.

2.5 Inventory Management Standards: ISO 14224 and NORSOK Z-008

Inventory management in the oil and gas industry necessitates a thorough and systematic approach for data consistency, reliability, and effective integration. In this context, the International Organization for Standardization (ISO) 14224 and the NORSOK Z-008 standards are of significant relevance and importance.

2.5.1 ISO 14224 Standard

ISO 14224 provides a comprehensive framework for the collection, exchange, and analysis of data related to equipment reliability and maintenance within the oil and gas industry. It offers clear definitions for taxonomy, data structure, and equipment classification, which prove invaluable in consistent and accurate data collection and analysis [25].

The ISO 14224 standard is crucial to the proposed inventory enhancement model as it ensures the data utilized for demand forecasting, safety stock calculations, and other inventory management techniques accurately represent the operating conditions. Moreover, it outlines guidelines for failure analysis, enabling a better understanding of factors impacting equipment performance and their effect on maintenance requirements [26].

2.5.2 NORSOK Z-008 Standard

The NORSOK Z-008 standard is specifically designed for criticality analysis for maintenance purposes. It provides a structured methodology for equipment classification based on the consequences of potential equipment failure, taking into account safety, environmental, and production impacts [27].

This standard is instrumental in this research for two key aspects: equipment criticality classification and risk assessment.

Equipment Criticality Classification: The NORSOK Z-008 standard includes a detailed system for classifying equipment based on its criticality and the implications of its failure. This classification system complements the ABC analysis, guiding the prioritization of spare parts for optimization efforts.

Risk Assessment: The NORSOK Z-008 standard also provides a structured approach for conducting risk assessments, helping identify and address potential risks linked to equipment failures and maintenance activities. This risk analysis is integral to the inventory enhancement model, ensuring all significant risk factors are considered during the process [28]. As part of the risk analysis, NORSOK Z-008 introduces the concept of unavailability, recognizing the importance of equipment availability in assessing its criticality [27].

In summary, the combination of the ISO 14224 and NORSOK Z-008 standards provides a robust framework for inventory management in the oil and gas industry, making them integral to the development and refinement of the proposed model. However, they are limited in their categorizations of classification, and this is evident in the case company's case due to the fact NORSOK Z-008 only focuses on demand rates only and not lead times, logistical issues, or high component costs in their classifications as shown in Figure 2.1 below.

Consequence / Demand rate	Low	Medium	High
First line spare parts, frequently used.	Minimum stock at site	Minimum stock at site and any additional spare parts at central warehouse	Adequate stock at site
Not frequently used.	No stock	Central warehouse, no stock at site	Central warehouse and minimum stock at site if convenient
Capital spare parts. Seldom or never used.	No stock	No stock	Holding optimized by use of risk assessment case by case

Figure 2.1: *Spare parts risk matrix [27].*

2.6 Stochastic Modeling

There are scientific approaches to spare part inventory management involving data-driven methods, such as the stochastic models, machine learning techniques, and simulation models, to make informed decisions.

Stochastic models consider the randomness of demand and lead times and are thus more realistic than the EOQ model [29]. Machine learning techniques, such as neural networks and support vector machines, have been used to predict the failure of equipment and thus the demand for spare parts [30]. These methods have shown promise but require large amounts of high-quality data, which may not always be available.

The model applied in this research will have some of the previously mentioned modeling adjectives but will be a stochastic modeling approach with some deterministic assumptions based on the data limitations, and therefore, these deterministic numbers are going to be based from direct sources within 'Company A'.

2.6.1 AnyLogic Modelling in Spare Part Inventory Management

AnyLogic is a leading simulation modeling tool. It supports system dynamics, agent-based, and discrete event simulation methodologies. Using AnyLogic for spare part inventory management in the oil and gas industry can provide a holistic approach that takes into account the interdependencies between different parts and systems, the variability in lead times and failure rates, and the criticality of different parts [31].

A key advantage of simulation modeling in AnyLogic is its capability to deal with real-life complexities and uncertainties in the model. The model can be validated and adjusted based on actual operational data, providing accurate and actionable insights [32].

It can be used to simulate various inventory management strategies (like EOQ, JIT, and ABC) and compare their performance under different scenarios, helping decision-makers to choose the most appropriate strategy for their specific situation [33]. It can also be integrated with machine learning models to further enhance its predictive capabilities.

This software is a very suitable choice for this research, given its multi-method modeling capabilities. These capabilities cover discrete-event simulation, agent-based modeling, and system dynamics, thus permitting the creation of intricate models that capture the multifaceted nature of inventory stock optimization challenges [34].

Discrete-event simulation is a modeling technique that simulates the operation of a system as a discrete sequence of events in time. Each event occurs at an instant in time and marks a change of state in the system. In the context of inventory management, discrete-event simulation could be used to model individual inventory transactions, such as orders, deliveries, and sales.

Agent-based modeling is another approach to modeling systems composed of autonomous entities or "agents," each with their own behaviors and interactions. This method is advantageous in capturing the behavior of individual tools and parts in the inventory, tracking their states, and monitoring their interactions with other parts of the inventory system.

System dynamics is a method for understanding the nonlinear behavior of complex systems over time. It deals with internal feedback loops and time delays that affect the behavior of the entire system. Within the context of inventory management, system dynamics can be used to model the high-level dynamics of the system, such as the relationship between demand, supply, and inventory levels.

Furthermore, AnyLogic offers a graphical user interface, facilitating visual representation of processes and results. This feature enhances the comprehensibility and communication of the model's structure. The software's flexibility supports custom code integration, enabling advanced algorithms' incorporation, such as intermittent demand forecasting techniques. Additionally, its built-in tools for designing experiments, executing simulations, and analyzing results pave the way for evaluating different scenarios and policies to pinpoint optimal inventory stock optimization strategies. The software's scalability ensures its applicability in managing large-scale models and simulations, rendering it suitable for modeling complex systems such as inventory management in the energy sector [35].

Chapter 3

Research Methodology

The methodology of research utilized a combination of quantitative methods, simulation modeling, and forecasting techniques to address the research objectives. The chosen methods were informed by the literature review and the specific context of the case company's operations. By following this methodology, the research aimed to provide valuable insights into the enhancement of inventory stock management and the streamlining of the maintenance process flow for the case company.

3.1 Scientific Research Approach

In order to comprehensively address the topic of inventory management enhancement within the context of this thesis, a rigorous scientific approach must be employed. This includes conducting a thorough literature review by utilizing resources such as Google Scholar to identify relevant articles, books, and past studies. Conducting interviews with experienced tool maintenance specialists within the case company and lecturers at the University of Stavanger (UiS) further supplement the knowledge base for this research.

In addition to gathering information from online and library resources, it is crucial to obtain pertinent data and documentation from the case company being investigated. This process requires a significant amount of time, as accesses to internal documents and datasets may be limited. To ensure the efficiency and effectiveness of the research, it is essential to differentiate between crucial and non-crucial data, and to focus on the aspects that are most relevant to the inventory management enhancement of the critical fleet tool under study.

3.2 Applied Methods of Research

In this research paper, the case study approach is utilized to investigate inventory management enhancement methods in a real-world context where we took a case company looking for ways to streamline their maintenance processes, while incorporating both quantitative and qualitative research methods. This combination of methods allows for a comprehensive understanding of the problem faced, facilitating the development of an effective inventory management model for the case company.

3.2.1 Case Study Approach

The case study approach is a widely used research methodology in various disciplines, offering researchers an opportunity to investigate a specific phenomenon or issue in-depth within its real-life context [36]. Case studies could be particularly valuable for exploring complex systems, generating hypotheses, and building theory. This research approach can incorporate both quantitative and qualitative data, allowing for a comprehensive understanding of the subject matter.

3.2.2 Quantitative and Qualitative Approaches Integrated

Quantitative research focuses on the systematic collection and interpretation of numerical data to describe, explain, or predict phenomena [37]. In the context of inventory management enhancement, quantitative research methods, such as statistical analyses and simulation models, are employed to analyze historical data, identify patterns, and evaluate alternative policies or strategies. Quantitative methods are particularly useful for providing objective, measurable, and generalised insights that can inform decision-making [38].

On the other hand, qualitative research emphasizes the collection and interpretation of non-numerical data, such as text, images, or processes to gain insights into the meanings, interpretations, and experiences of individuals or groups [39]. Qualitative methods, such as interviews, observations, or document analyses, assisted in exploring the contextual factors, organizational practices, and, therefore, helped construct the inventory management model for the case company. Qualitative research also helped create a more nuanced understanding of the underlying issues and generate insights that were not very apparent from quantitative data alone.

3.3 Research Design

The research design considered for this research is modeling, which is the most effective approach in the scope of this research since the output of it will address a future scenario on the spare parts inventory management problem. Its ability to handle the complex nature of the problem will facilitate the ability of decision-making under the presented uncertainties. It also allows the representation of all different factors such as demand patterns, lead times, and maintenance schedules in a structured manner, which further enables better understanding and analysis of system behavior. The model however required pragmatic measures, such as the limitation of considered tools to one only. This was also further limited to the top five critical components within the chosen tool.

In order to answer the research question ***"What is the effect of the repair-path cycle on the maintenance process flow implemented at the case company?"*** and achieve the research objective, a set of steps were established. These steps begin with analyzing the system at the case company, providing a conceptual model, a computational model, and making sure the model provides an accurate representation of the real-life system to validate the approach and provide the enhancement reliably. The steps are provided in Table 3.1 below for better illustration.

Table 3.1: *Methodology design steps*

Design Steps	Needed Data	Data Sources	Analysis Method	Validation
System Analysis	Company needs and evaluation criteria	Literature reviews and academic papers	Establishing problems and solutions of interest table	Tool specialist at case company
Conceptual model	Maintenance processes at case company	Case company work flow documents	System mapping flowchart	Academic supervisor
Computational model	Model inputs from data collection	Case company input data	Anylogic Software	Tool specialist at the case company
Verification & Validation	Validation criteria of model logic and outputs	Result plots and expert opinions	Simulation experiments for the model and checking different model outputs	Tool specialist at the case company

3.4 Development of model

Through utilizing AnyLogic for modeling the spare parts inventory management issues and bottlenecks, organizations such as the case company, can leverage its powerful features to gain valuable insights, identify optimal strategies, and continuously improve their inventory management practices. The modeling was mainly deductive from the theories and literature, however, in certain situations, inductive measures were taken to produce a practical model that accounts for the enhancements applied.

To begin, a set of key performance indicators should be kept in mind while building the model. This included the maintenance lead times, worker utilizations, crowding levels, and overall costs and financial parameters demonstrating feasibility and providing valuable feedback for continuous improvement efforts of procedures. The aim towards meeting operational demands needs an inventory management model to be developed where an integration of the theoretical approaches and scientific methods discussed in this research are applied.

The model should consider a set of elements, such as the demand forecasting, ABC analysis, Stochastic inventory modeling, stock management, and accounting for risk management.

The model's structural methodology encompasses several critical components. Starting with accurate demand forecasting, which is achieved through time series analysis using Python code that incorporates the modified Croston's method by TSB, is critical for optimal inventory management, as it enables the prediction of future spare parts demand. The ABC analysis categorizes spare parts based on importance, facilitating the prioritization of process enhancement efforts and resource allocation.

Moreover, with a stochastic inventory model, service level constraints are accounted for through the separation of maintenance requirements for each tool's needs. The model also accounts for uncertainty in demand rates and lead times, resulting in more robust inventory policies tailored to the case company's unique characteristics once established and optimized. This way a baseline and an enhanced model can be developed, verified, and validated.

Once the baseline model is established, the enhanced model will be built including the same input parameters such as the placement of the same re-order points for the critical spare parts. Of course, while taking into consideration the above-mentioned factors such as demand and lead time variability, service level requirements, and cost trade-offs, which will in theory still result in more streamlined maintenance processes by minimizing equipment downtime and reducing maintenance time and costs.

Finally, the inclusion of risk management strategies within the modeling approach of the enhanced model will be able to mitigate supply chain disruptions' impacts and enhance the inventory management system's overall resilience [40]. This is done through the establishment of a repaired stock that in turn will be utilized as a main stock, while the new build stock is placed as a safety stock.

Chapter 4

Data Collection

This chapter contains the approaches of collecting the case company's data, the parameters taken into consideration, standards used for guidance, as well as presenting and illustrating them, all while protecting the Intellectual propriety belonging to the company to the highest reasonable level.

4.1 Case Company Data

All data used in this research was collected from the case company, including information on demand patterns, lead times, maintenance frequencies, maintenance lengths, procurement costs, and other relevant factors for the selected components. The data collection process involved close collaboration with the case company to ensure the accuracy and completeness of the data. However, gaps naturally occurred within the data, but that did not stop the model from reflecting a real view on the processes. The gaps within the data were substituted by values suggested by the tool specialists within the department, such as the procurement lead time which varied a lot with the COVID-19 occurrence and was no longer a true representation of these lead times.

4.1.1 Data confidentiality

Data Confidentiality of the collected data was maintained throughout the research process upon their request, and therefore, the model is built based on their case, but can be utilized for other maintenance facilities. Any personally identifiable information or sensitive data will be anonymized or encrypted to ensure privacy.

4.1.2 Data Verification and Validation Approach

Data Validation prior to analysis involved checking for completeness, consistency, and accuracy. This was performed systematically, where continuous interviews took place with various representatives in the department. Data verification, on the other hand, ensured that the collected data accurately represented the real-world current scenario. Any inconsistencies or missing data were addressed and rectified through collaboration with the case company to set assumptions or estimates.

4.2 Equipment selection approach

The research aimed to gather reliable and comprehensive information necessary for the spare parts inventory management analysis. ISO 14224 standard provided a hierarchical classification system for equipment, which classified the spare parts and components used in the research. This classification system enabled a consistent and organized approach to data collection, allowing for easier comparison and analysis. The use of this standard helped set the data elements and their attributes that should be collected for each component. These data elements include information such as equipment identification, maintenance history, failure data, and repair information. By following the defined data elements and attributes, the research verified that all relevant information was captured uniformly.

The standard offered guidelines for data collection methods, including recommended data sources and collection techniques, and therefore, emphasized the importance of data quality management throughout the data collection process. Overall, it assisted with data validation, verification, and quality control measures to keep the accuracy, completeness, and reliability of the collected data, gaining robustness of the subsequent analysis.

4.2.1 Equipment selection

To begin with the select data description, it is worthy to note that there were various changes happening with the ERP (Enterprise resource planning) systems storing historical maintenance and procurement data before 2021. This caused the quality of all data before that year to be lower, as it was not possible to access the older systems. However, there was enough data to narrow down the flagship of the fleet, or in other words, highlight the highest utilized tool with the shortest maintenance turnarounds.

This specific tool faced issues in meeting project demands due to the lack of components, causing expedited repairs, or expedited procurements, estimated to triple each of these costs according to the tool specialist. Its components are by far the costliest for the business to replace had any major failure occurred. Overall, it happened to have the highest operational velocity with approximately 4 operations per tool a year. As well as the costliest core components, and high component consumption rates meaning significant scrap rates.

This tool was by far the most complicated, holding over 50 different components within. In this research, the top five critical components were chosen for the analysis. For the sake of this research, this tool is referred to as 'Tool A'. The tool has two different component types, core components, and standard replacement parts. The standard replacement parts were directly excluded from the focus of this research due to the case company having a lot of preparedness towards it.

4.2.2 Component selection

When it came to the core components, the most critical components selected were tagged confidentially as to further maintain the data protection for the company. These tags range from 'Comp. 1' till 'Comp. 5'. They were chosen based on a conducted ABC Analysis to identify and select the components to be modeled. The components were classified into three categories (A, B, and C) based on their annual usage value, which is calculated by multiplying the annual consumption by the unit cost.

Moreover, procurement lead time was accounted for as a fixed average determined for each component range based on sourcing specialist inputs. The HSE criticalities on operations stemmed from the NORSOK Z-008 standard categorization of consequences illustrated in Chapter 2. Once categorized, Category A represented the most critical components with the highest annual usage value, while Category C consisted of the least critical components with the lowest annual usage value. The analysis allowed for the prioritization of the components and informed the focus of the research.

For better illustration, Table 4.1 is presented below with the consumption rates and cost of procurement found directly from the historical data. This gave an indication of the annual costs being accumulated on the business due to the failures of these components. Therefore, it consistently narrowed down the range till the top five were chosen and analyzed.

These 5 components had their re-order quantities set by the department, and their minimum (min.) and maximum (max.) stock values manually set as well. The minimum and maximum stock values presented the current range of stock for a tool, where if it falls below the minimum, an order is placed with the re-order quantity, and this is further allowed as long as the stock quantity does not exceed the current maximum set value.

Their consumption rates were driven from the old ERP system and the new one implemented in 2021. Though the average procurement costs were driven from the previous orders, these costing values were modified with a multiplication factor to avoid any traceability to the real company data. Collectively, these parameters and values provided a comprehensive overview of the inventory stock levels and procurement practices for the selected components. They served as a foundation for the subsequent analysis and enhancement efforts in improving the overall inventory management system.

Table 4.1: *Selected components from historical inventory values.*

Tag name	Re-order Quantity	Min//Max stock	Replacements in 2021/2022	Previous 5 years replacements	Cost of procurement
Comp. 1	1	3//5	7	17	260,000 NOK
Comp. 2	1	3//4	10	15	310,000 NOK
Comp. 3	1	3//4	10	18	134,000 NOK
Comp. 4	2	3//5	10	17	27,200 NOK
Comp. 5	1	1//2	8	14	34,000 NOK

The overall data was obtained from a data dump consisting a workshop capacity of five workers with enough expertise to maintain “Tool A” over a total of 130 total maintenance visits taken from the new ERP system, where 89 of these visits were used maintenance on the tool, 41 were unused, and 45 total critical components having issues on core components from the top selected five in the years 2021 and 2022. There were some difficulties with the repair tracking data of components in the currently implemented system at the case company, so it was assumed 60% of used visits have at least one repair issue based on the tool specialist interview. These values were ratioed out from the total visits obtained historically and further dissected to be implemented within the model built.

4.3 Demand data

The collection of accurate and reliable demand data was crucial for conducting a comprehensive analysis of the case company's inventory management. In this research, demand data was collected over a period of four years, specifically from 2019 to 2022, to capture a significant timeframe and account for potential variations in demand patterns. It focused on gathering information on the demand for the selected 'Tool A'.

It is worth noting that the demand data exhibited intermittent patterns, with instances of zero demand occurring due to the inconsistent operations during the COVID-19 pandemic. Below, Table 4.2 presents an illustration of the intermittent demand occurring in case company which will be further discussed and analyzed in the following chapter.

Table 4.2: *Historical demand data.*

DEMAND													
Year	Month	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
2019		**7**	**2**	**5**	**7**	**9**	**2**	**8**	**4**	**3**	**4**	**1**	**3**
2020		**3**	**3**	0	**7**	0	0	**6**	**2**	**4**	**5**	**2**	**3**
2021		**3**	0	4	**6**	**7**	**2**	**5**	**6**	**3**	**3**	**6**	**2**
2022		**3**	**5**	**2**	**6**	**6**	**9**	**1**	**10**	**4**	**9**	**11**	**10**

Chapter 5

Analysis

The chapter aims to detail the conceptual and computational analyses performed in order to build the simulation baseline model and the enhanced model. The forecasting method and the financial analysis are both present in this chapter. A validation and verification section is provided at the end of the chapter.

5.1 Analysis Approach

The inventory management enhancements applied for the selected components in the research can be a complex problem. This is due to the several factors playing a role in the high maintenance costs and long lead times. After establishing the methodology approach previously in Chapter 3, and constructing a solid framework for collecting data in Chapter 4, it is in fact, the analysis that ties it all together. The analysis was performed conceptually first, followed by the two different software systems, being Python and Anylogic for implementation.

The collected data was analyzed using various techniques, such as descriptive statistics, trend analysis, and data visualization, as to gain better understandings of the currently implemented inventory management system and maintenance process flow. The analysis aimed to identify patterns, trends, and potential areas for improvement in the case company's operations. This drove the research to a narrowed section of the fleet, and therefore identified the most applicable tool with the highest maintenance costs and operational demands to be chosen, and further analyzed, being 'Tool A'.

5.2 Problem of Interest

To understand the issue this analysis is revolved around, a table was created to highlight the main drawbacks of the current maintenance process for 'Tool A' where there are elongated lead times within the tool maintenance, having several implications. The problem is identified by tool specialists and department manager within the case company. It is considered problematic because it affects offshore operational demands, does not contribute to revenue improvement, and leads to high maintenance costs. The problem is primarily observed at the maintenance facility (Workshop), and its impact is felt by offshore operations customers, case company employees, and asset owners. The issue has been observed over several years of operation and is detected through data analytics and historical maintenance data. The root cause of the problem is further identified as the lack of proper inventory stock management, which is what this analysis will focus on. The Table 5.1 provides an easy to comprehend overview of the problem of interest.

Table 5.1: *Problem of interest.*

Aspect	Description	Source
What is the problem?	• Long lead time of tool maintenance • Chance to reduce maintenance costs	• Tool specialists • Department manager
Why it is a problem?	• Affects offshore operational demands. • No improvement of revenue. • High costs of maintenance.	• Tool specialists • Data analytics
Where is the problem observed?	• Maintenance facility	• Case company
Who is impacted?	• Offshore operations customers • Case company employees • Asset owners	
When was the problem first observed?	• After several years of operation	• Tool specialist
How was the problem observed?	• Data analytics	• Department manager

How often is the problem observed?	• Multiple times annually	• Data Analytics
What is the root cause of the problem?	• Lack of inventory stock management	

5.3 Solutions of interest

Having now identified the problems faced within the case company's maintenance process, there are proposed approaches to reduce the lead time, however these proposed solutions come with investment costs. This is the reason it is critical to identify the best position for the case company to take. It is the aim to reduce the overall lead time, and also reduce the maintenance costs on the long run. Based on the tool specialist's input on site, it was clear that the approach needed to include structural changes. This is due to the fact that the having unlimited stock of components would merely not make any profitable sense to do. This is why the first proposed solution of interest involved changing the structural process of component repairs, where a component is automatically shifted out of the tool once identified as faulty and replaced with another repaired or new component depending on the current stock levels at the time. This proposed way involved a cyclic path of bulk repairs that future proofs the components in a way where the component undergoes repair on the areas with issues and further repairs on the remaining potential areas where historical data showed repairs on. It is more than just a repair path cycle, but a future proof of failure that will in return reduce the failure rates over the coming two years and eliminate any repair lead time. Once the faulty component is removed and replaced, the tool keeps going unaffected by it and therefore meets all operational demands with ease, just as if it had no faults at all.

The second proposed solution depends somewhat on the first, where after this implementation, and the sudden rise in demand happens, there would be contingency planning in the manner that a local manufacturer would be able to supply the new build components instead of the best cost country one. These shorter procurement lead times when components are unable to be repaired would help meet unexpected rises in operational demands. However, that would multiply the cost of procurement and accumulate high maintenance costs, so this solution will not be the focus of this research. The two solutions are presented in Table 5.2 below for better visualization.

Table 5.2: Solutions of interest.

Change	Function	Rules	Processes	Properties
Set up the repaired path cycle and integrate it into the maintenance process.	Automatically transfer the component out of the tool and onto a separate pathway that fixes it.	An accumulation of 3 faulty components activates it to reduce cost of repair through bulk repairing	Receive and future proof faulty components.	Returns the future proofed components to the newly added repaired stock.
Changing the manufacturing vendor.	Tools components are sourced in reduced amounts of time	When an order comes through, it goes through the modified delay of supply.	Receive order, check if it is processed, then return it to stock inventory.	Reduce the delay time between orders.

5.4 Conceptual modeling

A detailed system mapping was developed to conceptualize the flow of materials, information, and decision-making processes involved in the inventory management. The interactions between the workshop, warehouse, maintenance activities, and operational demands are identified and analyzed. The system mapping provided a holistic view of the inventory management process and facilitated a better understanding of its complexities.

5.4.1 Baseline system mapping

For the existing baseline case process, the workflow starts with the return of the tool from offshore operations to the workshop. Upon receiving the tool, the workshop personnel perform a disassembly if it was used, otherwise, a cleaning process is carried out. During the disassembly process, standard replacement parts are installed into the tool if no issues are detected by the quality controllers. However, the effectiveness of the inventory stock management system is put to the test when issues are identified and components require repair. At this point, the tool remains idle, waiting for the faulty part to be repaired, resulting in significant lead time delays that directly impact operational demands. Figure 5.1 provides a visual representation of the current process, highlighting the steps involved in the tool's journey from offshore operations to the workshop and the subsequent repair and maintenance stages, till it is back offshore.

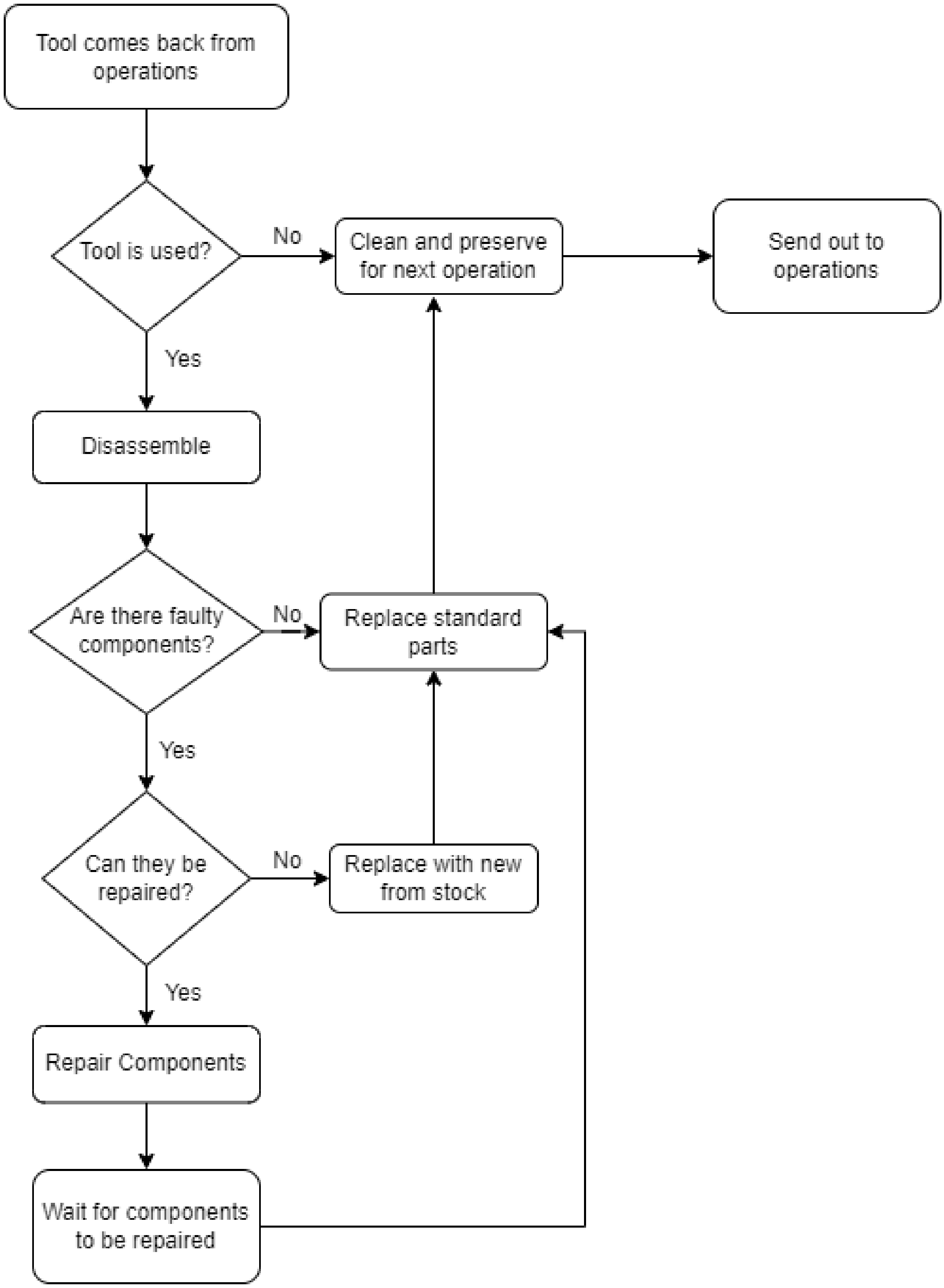


Figure 5.1: *System mapping for current process*

5.4.2 Enhanced system mapping

The objective of this research is to address the identified issue by implementing a solution that enables the dispatch of tools within seven working days from their receipt, thereby streamlining the repair process and minimizing unnecessary lead times. To effectively map this process, it is important to emphasize that several steps overlap. This includes the initial identification of the tool, regardless of whether it has been used or not. For unused tools and used tools without any faulty components, they follow the same route as the current baseline process.

Significant structural changes occur when a tool is identified as having issues. This triggers a component change, regardless of the level of repair needed. The tool then proceeds through the maintenance flow, while the faulty component is added to a batch, which in turn gets sent for service and repair once a quantity of three is reached. The process concludes with an inspection of the repaired tool, which is then returned to the repaired stock for future utilization on tools that may experience the same component failure. This approach ensures the future-proofing of the component while lessening the need for undue pressure on supporting functions to expedite repairs and shipping.

To provide a visual representation of the enhanced process, Figure 5.2 is included below, offering a clearer illustration of the steps involved in the tool's journey, including the identification, repair, and return of components to the stock. This depiction helps to visualize the proposed enhancements to the existing process.

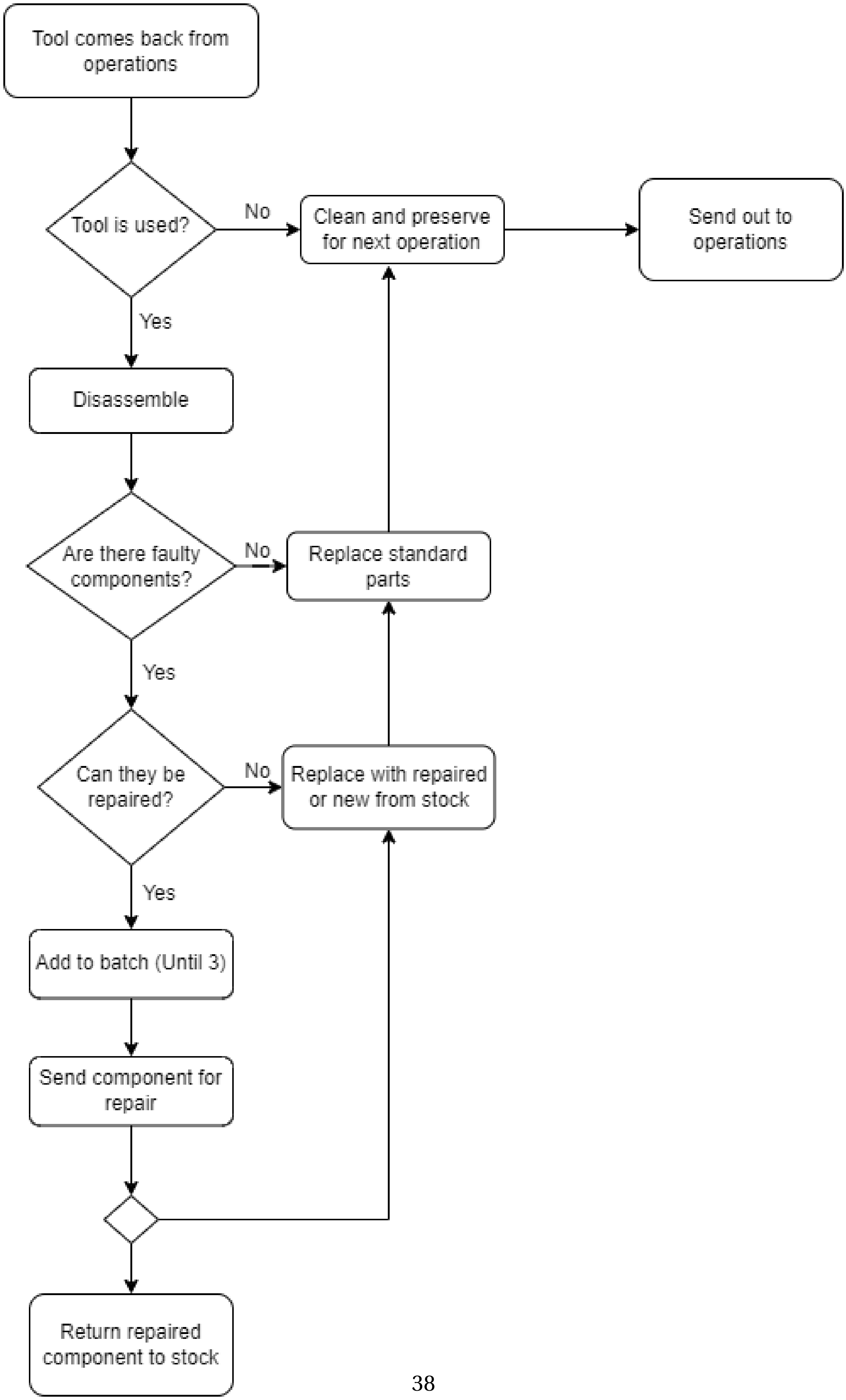


Figure 5.2: *System mapping for the enhanced process*

5.5 System planning

The purpose of the simulation model is to provide a reflective analysis of the current maintenance processes and propose suggested improvements through scenarios. This is tackling the research question at hand being *"how the repair-path cycle be modeled practically to illustrate the operational behavior in terms of lead times and operational efficiency?"*

To begin, the main key performance indicator (KPI) that will be visualized in the simulation model is the lead time for tool maintenance. This metric will serve as a measure of efficiency and effectiveness in the maintenance process. This will further be discussed and evaluated in contrary with the cost of investment and implementation goes back to the decision-makers.

The model boundary is primarily focused on the workshop process, with the individual components (1 to 5) considered as separate agents. Additionally, the "main" agent encompasses most of the maintenance process, capturing the overall workflow and interactions among the various components. The model time unit is measured in hours, and the time horizon for the simulation is based on 3-year timeframe. This allows for a comprehensive analysis of the long-term performance and trends within the maintenance process.

In terms of scenarios, the prime scenario considered is the integration of the repaired-parts cycle process within the maintenance process. This will reflect on varying factors such as lead time of maintenance, inventory stock shortages, workshop capacity utilization, and financial feasibility through profit margins. These factors will help evaluate the overall performance of the enhanced maintenance process.

To ensure the accuracy and reliability of the simulation model, various verification and validation activities are planned. Verification will involve comparing the computational model with the conceptual model to ensure that the model functions correctly. Validation is conducted through interviews with tool specialists at the case company to validate the representation of the real system in the computational model. Additionally, input data was carefully verified to ensure its accuracy and consistency with the actual system. As means of illustration, Table 5.3 is presented below to summarize the key points tackled within the system planning.

Table 5.3: *System planning structure.*

What is the purpose of the simulation model? What is the research question to be answered?	• To reflect on the current processes of the maintenance process and present desired improvements through suggested scenario.
What are the main KPIs that will be visualized?	• The lead time of the tool maintenance.
What is the model boundary?	• The model's focus is on the workshop process, and the considered agents are components 1 to 5 (confidential naming), making each component a separate agent, and the "main" which includes most of the maintenance process.
What is the model time unit, time horizon and level of details?	• The model time unit is hours, and the time horizon is yearly based.
What are the considered scenarios or experiments?	• Installing the repaired path cycle process within the maintenance process is going to be the scenario.
What are the planned verifications and validation activities and data sources?	• For the verification, comparing the computational model and the conceptual model to see if the model works correctly. • For the validation, checking if the computational model presents the real system accurately by conducting interviews with the tool specialist at the case company and verifying the input data.

5.6 Analyzed components

There exists three different set of components within 'Tool A'. Due to the confidentiality of the Intellectual Property of the company, the ABC analysis categorization vaguely described what they represented in the data collection chapter (Chapter 3). However, components that were inputted into the structure of the model, were among many from which were categorized between A, B or C.

Category A represented the modeled five components that fit into the highest cost of consumption yearly. Category B defined the rest of the components that did not fit into the top five, but still pose a threat on the maintenance lead time of the tool where any of their unavailability still defies and jeopardizes the streamlining of the maintenance processes. Ideally, Category B should be included within the model, but due to time and funding restrictions of the research, Category B was neglected, and this leaves room for further improvements.

Finally, Category C represented the standard replacement parts, which were neglected due to the high frequency of their changes and therefore, have very high preparedness levels by the Case Company, who allocates them efficiently. Table 5.4 below provides an informative visual illustration of the criticality of each category ranging from the lowest criticality being 'Low', to the highest criticality being 'High', and 'Medium' in-between.

Table 5.4: *Criticality categorizations.*

Category	Cost	Consumption Rate	Lead Time	HSE criticality offshore
A	High	Medium	High	High
B	Medium	Medium	High	High
C	Low	High	Medium	Medium

5.7 Tool demand forecasting model

A python model was constructed on the basis of forecasting the upcoming smoothed demand months from the end of the input monthly coming from Chapter 3 demand data obtained through the case company. It is basically an implementation of the Teunter-Syntetos-Babai (TSB) modification of Croston's method. The TSB modification builds on the original Croston's method by introducing separate smoothing parameters for demand size and inter-demand interval and updates these parameters differently based on whether a demand occurs or not.

To begin, the Croston_TSB function starts by setting up the necessary data structures and initializes the level (a), probability (p), and forecast (f) arrays. It first identifies the first non-zero demand in the time series and uses it to initialize a[0], p[0], and f[0]. This approach follows the TSB method's original assumption of a demand occurrence at t=0, which is used to initialize the parameters.

The function then loops over the entire historical time series. If a demand is registered at time t (demand > 0), it updates the average demand (a[t]) using the alpha 0.1 smoothing factor and the probability of demand (p[t]) with a fixed beta 0.1 smoothing factor. This allows the inter-demand interval to update immediately upon the occurrence of demand.

If no demand occurs (demand = 0), the average demand (a[t]) remained unchanged, while the probability of demand (p[t]) was updated according to the (1-beta) factor. This allowed the model to gradually neglect zero demand periods and give more weight to recent inter-demand intervals. The function also produced a forecast at every time step by multiplying the current estimates of a[t] and p[t]. For future periods, it carried forward the last known values of a, p, and f from the historical periods.

Finally, the function returned a pd.DataFrame that included the original demand, forecasted values, level (a), probability (p), and forecast error (Demand - Forecast) for every period in the time series. This output allowed for a comprehensive breakdown of the model's performance, including bias, and other aspects.

It is important to note that any forecasting model, has its effectiveness dependent on the nature of the demand data and the appropriateness of the chosen smoothing parameters alpha and beta. They should be selected based on cross-validation or other model selection procedures to ensure the best forecasting performance, but for the purpose of this research, the alpha and beta smoothing parameters were merely assumed in line with the recommendation in the scientific literature. A representation of the model code is presented below in Figure 5.3.

```
import numpy as np
import pandas as pd

def Croston_TSB(ts, extra_periods= 5, alpha= 0.1, beta= 0.1):
    d = np.array(ts)
    cols = len(ts)  # Historical period length
    d = np.append(d, [np.nan] * extra_periods)  # Append np.nan into the demand array to cover future periods

    # Level (a), probability(p), and forecast (f)
    |
    a, p, f = np.full((3, cols + extra_periods), np.nan)

    # Initialization

    first_occurrence = np.argmax(d[:cols] > 0)
    a[0] = d[first_occurrence]
    p[0] = 1 / (1 + first_occurrence)
    f[0] = p[0] * a[0]

    # Create all the t+1 forecasts

    for t in range(0, cols):
        if d[t] > 0:
            a[t + 1] = alpha * d[t] + (1 - alpha) * a[t]
            p[t + 1] = beta * (1) + (1 - beta) * p[t]
        else:
            a[t + 1] = a[t]
            p[t + 1] = (1 - beta) * p[t]
        f[t + 1] = p[t + 1] * a[t + 1]

    # Future Forecast
    a[cols + 1 : cols + extra_periods] = a[cols]
    p[cols + 1 : cols + extra_periods] = p[cols]
    f[cols + 1 : cols + extra_periods] = f[cols]

    df = pd.DataFrame.from_dict(
        {"Demand": d, "Forecast": f, "Period": p, "Level": a, "Error": d - f}
    )
    return df


# Sample demand data
demand_data = [
    7, 2, 5, 7, 9, 2, 8, 4, 3, 4, 1, 3, 3, 3, 0, 7, 0, 0, 6, 2, 4, 5, 2, 3, 3, 0,
    4, 6, 7, 2, 5, 6, 3, 3, 6, 2, 3, 5, 2, 6, 6, 9, 1, 10, 4, 9, 11, 10,
]

# Croston's TSB method applied to the sample data
extra_periods = 6
forecast_df = Croston_TSB(demand_data, extra_periods=extra_periods)

# Print the forecasts for the next periods
print(forecast_df["Forecast"][-extra_periods:])
```

```
48    6.143295
49    6.143295
50    6.143295
51    6.143295
52    6.143295
53    6.143295
```

Figure 5.3: *Python model for forecasting demand*

5.7.1 Forecasting model visualization

The demand forecasting model was validated using cross-validation measures, such as Mean Absolute Error (MAE). The validation process ensured the reliability and accuracy of the forecasts generated by the model. The end result was then plotted in Figure 5.4 below to show the smoothed forecasted demand in comparison to how the historical demand was over the periods of 2019 to 2022, stemming from the obtained case company's historical demand data. The model was able to successfully smooth the historical demand and produce a smoothed future forecast of 6.143295 monthly demand.

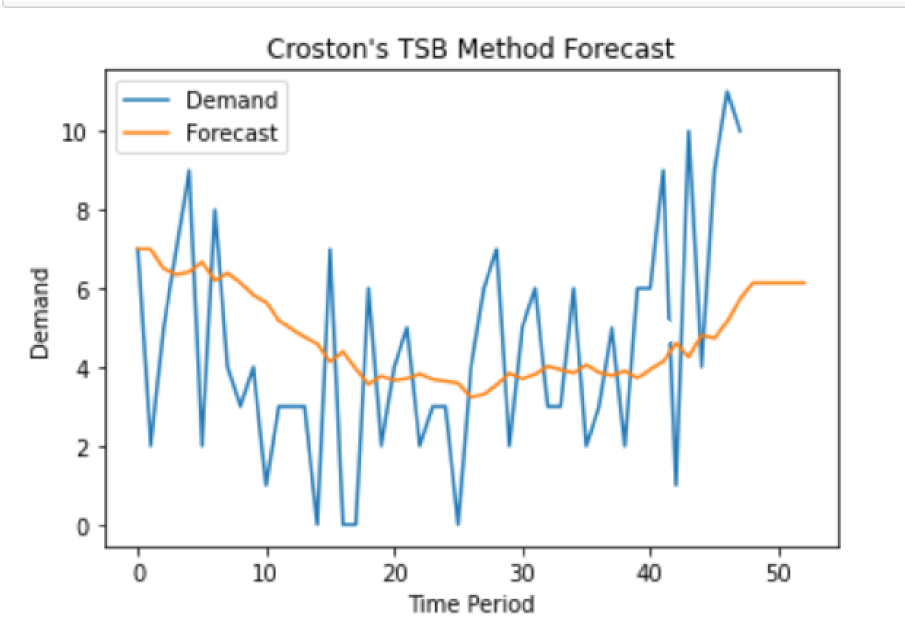


Figure 5.4: *Forecasted demand graph*

5.8 Baseline Model

An AnyLogic baseline model was developed to simulate the existing inventory management process for the five core components. The model incorporated the demand forecasts generated by the Python model, as well as the stochastic inventory management enhanced techniques. The input parameters, assumptions, and constraints of the model were carefully defined based on the case company's data and operational requirements identified within Chapter 3.

The model structure started off by building the "main" agent which represented the current process flow of maintenance within the workshop of the case company, where each stage was represented by a discrete event as presented in Figure 5.5 below. The tool is modeled in a way where it comes into the workshop through a source, gets identified if used or unused. Once that is identified, the tool is then either taken for unused cleaning and preservation, or disassembled if found used. After disassembly, the tool is then determined if it has issues, no issues, or needs component replacement. If no issues are found, the tool proceeds for standard used maintenance, but if repairs are needed, the tool is stored in the workshop shelves as the component gets outsourced repairs. However, if the tool needs component replacements, then the tool gets the component replaced if it is on stock, or sits and wait for the component to arrive causing delays. Once any of the used tool possible outcomes is satisfied, the tool is ready for assembly, and is then sent out to operations through the sink.

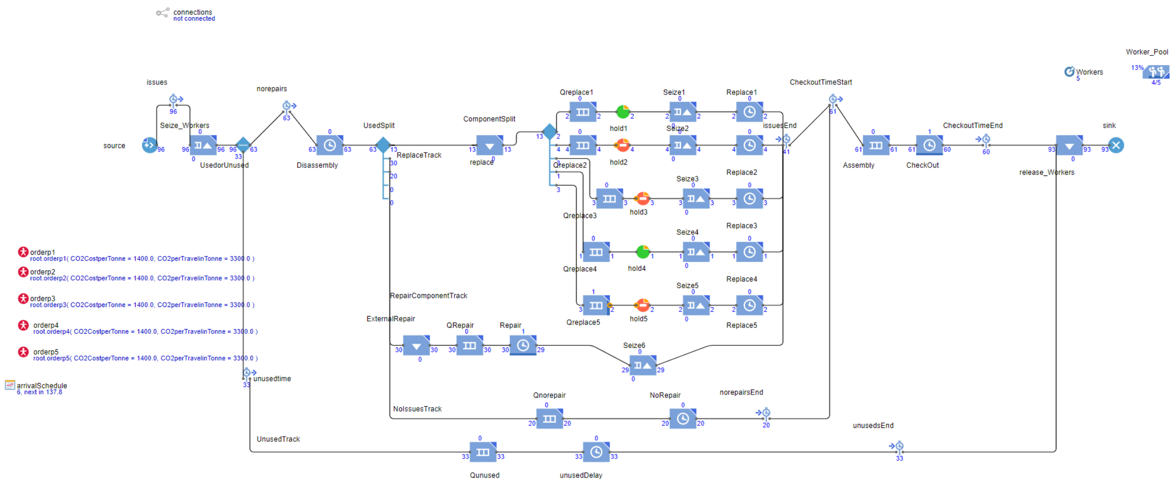


Figure 5.5: *Baseline model maintenance process flow*

The discrete events started off with the “source” which represents the source block. The arrivals are defined by the rate schedule, and its rate schedule is set in a way that pulls in the demand data from the “arrivalSchedule”. This is shown below in Figure 5.6 for better visualization.

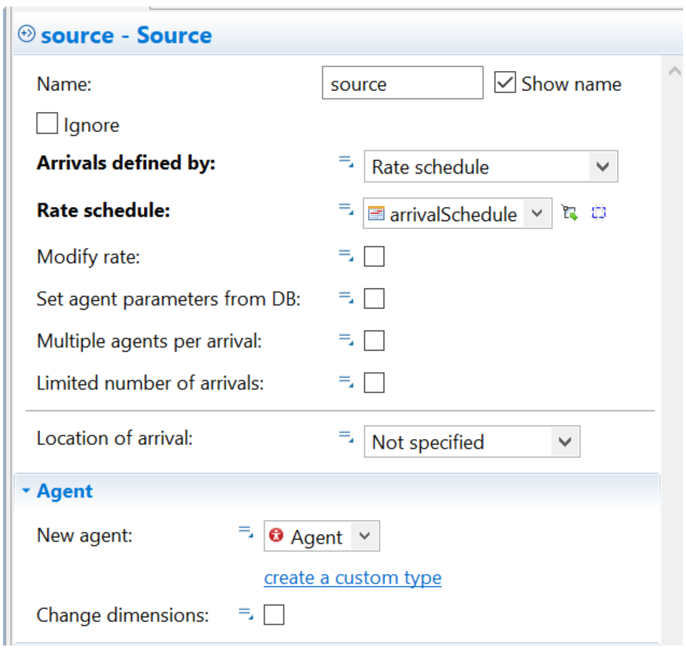


Figure 5.6: *Source parameters*

The “arrivalSchedule” is a schedule block that allows the model to have repeated inputs based on a timeframe defined. For this model’s schedule, it was set up in accordance to forecasted demand from Python, which was then smoothed into a whole number. This was done through considering every seventh month to have a demand of 7.0 while the other six months have a demand 6.0. The schedule was defined by type Rate, and a monthly unit meaning it is a probabilistic approach to demand expectation. It was then set to define moments and not intervals, as well as to repeat every month consistently throughout the model time by selecting custom duration to repeat every month till the end. The data was then inputted into the table which had two columns being the "Time" consisting of 12 monthly entries and consecutively 12 "Values" to be entered. The value being the demand of tools incoming. Month 1 and month 8 had a demand of 7.0 while the rest had 6.0. This is better represented in Figure 5.7 below.

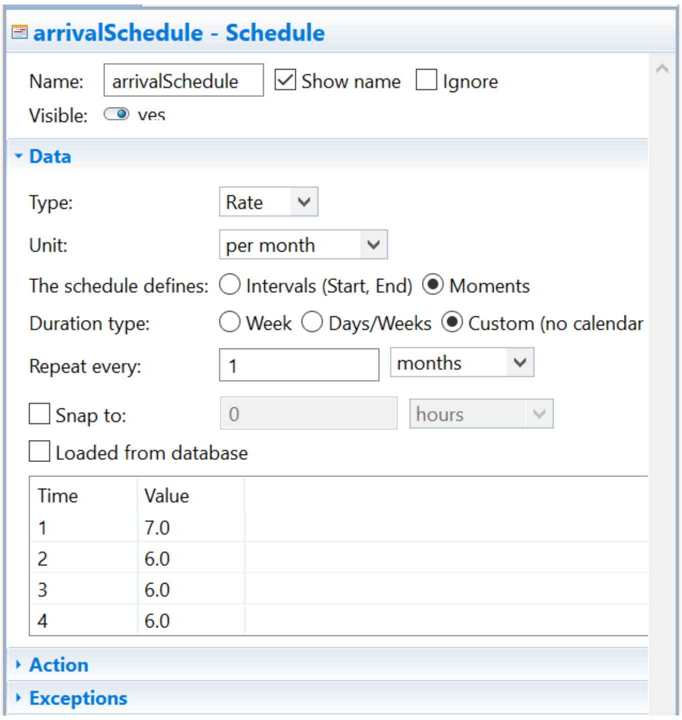


Figure 5.7: *Arrival schedule for tools*

After the tool is received in the workshop, there are timer starters represented in four different TimeMeasureStart functions being "issues", "norepairs", "unusedtime" and "CheckoutTimeStart". These functions are defined by a Single agent, and are measuring each different process of maintenance. The "issues" is to measure the tool with issues that can't be repaired and measures any lead time delays from stock outages. The "norepairs" measures the standard maintenance process time length for used tools with no unexpected component failures. Moreover, "unusedtime" measures the lead time for all quick maintenances done on the unused tools. And finally, the "CheckoutTimeStart" measure the assembly time of tools for all used tool maintenance jobs. For better illustration, one of them being the "repaired" is represented in Figure 5.8 below.

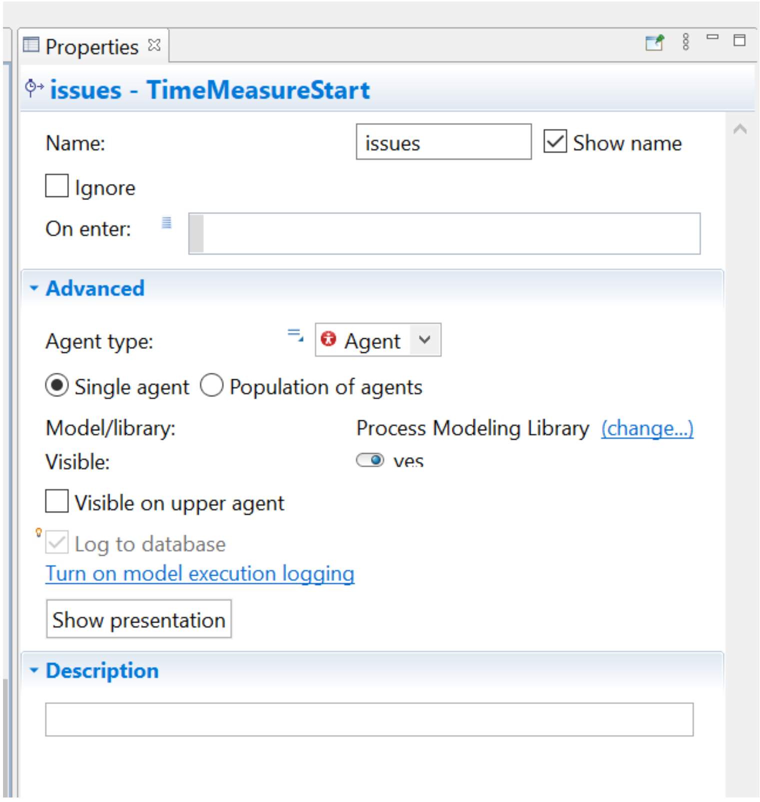


Figure 5.8: *TimeMeasureStart properties*

These TimeMeasureStart blocks are then followed by corresponding TimeMeasureEnd blocks in order to end the time measurements of these processes. There are four blocks in total, and they are corresponding to each of the TimeMeasureStarts. The "issuesEnd" block is linked to "issues", similarly, the "norepairsEnd" is linked to the "norepairs", the "unusedsEnd" is linked to "unusedtime", and the "CheckoutTimeEnd" is linked to "CheckoutTimeStart". They all have similar Dataset capacity of 100, meaning they can measure a total of 100 tools simultaneously as an overexaggerated value to not miss any tools not being measured. An example of the "issuesEnd" is presented below in Figure 5.9 to better show how it is constructed in the model.

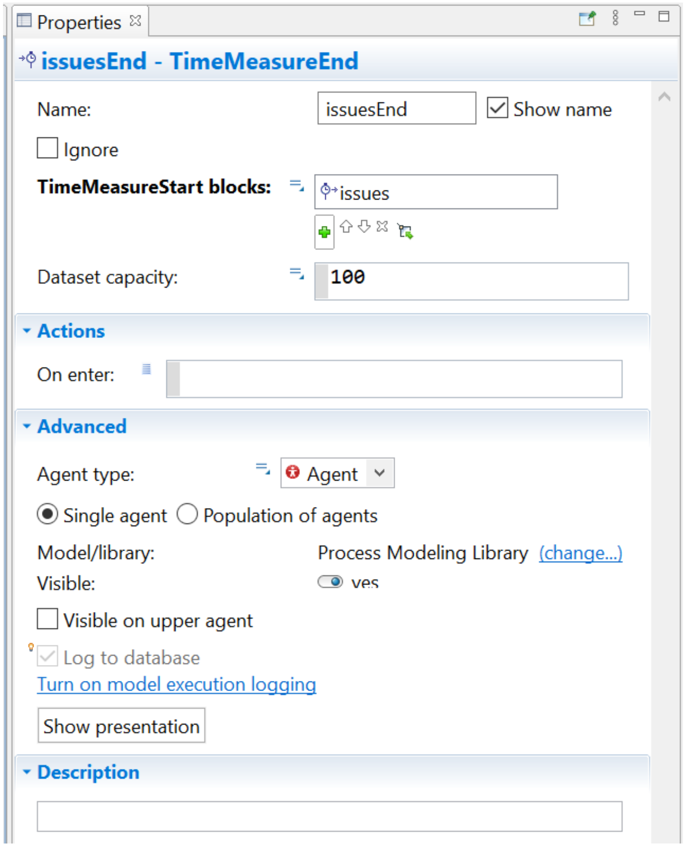


Figure 5.9: *TimeMeasureEnd properties*

The model is built on the basis of the case company's workshop, therefore, the seize block is accounted from the workshop capacity where it takes a worker from "Worker_Pool" ResourcePool for the job. The worker that way is booked for the job regardless if it used, unused, with issues or without. The Seize is built upon a ResourcePool, and the ResourcePool is taking its values from a defined parameter called "Workers" that is accounted for from the real workshop capacity at the case company. A summary of the seizing set used in the model is presented in Table 5.5 below.

Table 5.5: *Seizing of workers.*

Block name	Functions	Properties
Seize_Workers	Seize	• Resource set: "Worker_Pool" • Queue Capacity: 200
Worker_Pool	ResourcePool	• Capacity: "Workers"
Workers	Parameter	• Default value: 5

Once the tool is received, and the time is accounted for, then the tool is identified whether it is used or unused. That is done using a SelectOutput block named "UsedorUnused" in the model. Through that, a probability is inputted stemming from the data collection where the number of tools being used historically out of the total visits in the data collection are ratioed out and that probability being 0.685 is then implemented to be the probability of the tool being used from offshore. To illustrate how this block works, the Figure 5.10 is presented below.

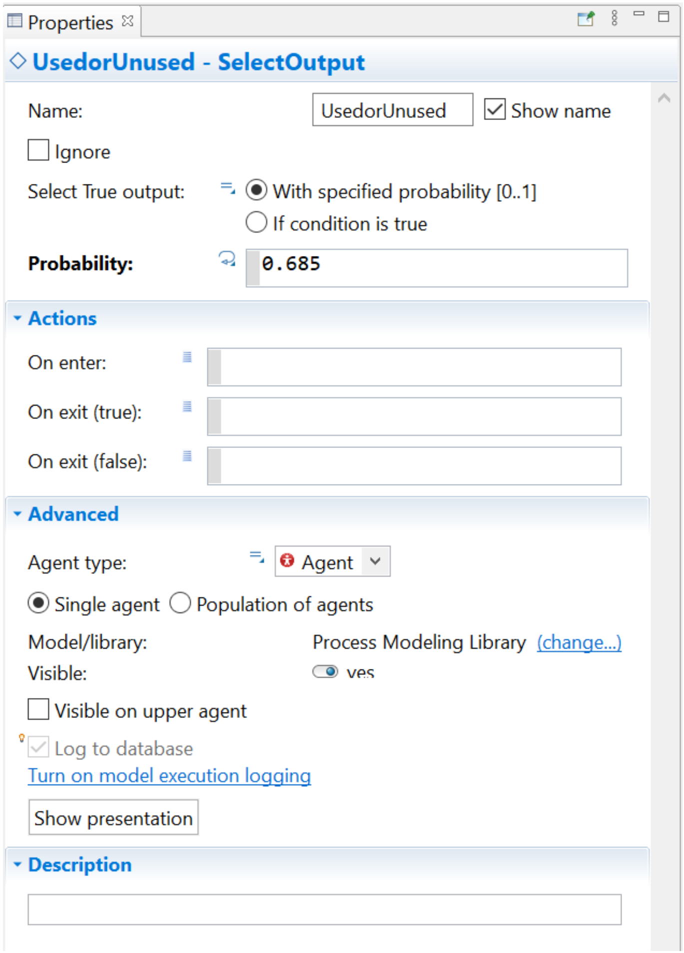


Figure 5.10: *UsedorUnused SelectOutput*

If the tool is identified as unused, there is a track that separates it following the "UsedorUnused" SelectOutput which takes then the tool through a defined track made up of two different blocks before being redirected to the Release block "release_Workers" in order to exit. It starts with the Queue followed by the Delay to perform the needed cleaning and preservation of the tool, and finally is connected to the Release block in order to free up the worker to start on a new tool. The Table 5.6 below details this track's parameters.

Table 5.6: *UnusedTrack blocks.*

UnusedTrack blocks	Functions	Properties
Qunused	Queue	• Maximum capacity • Queuing: FIFO
unusedDelay	Delay	• Maximum capacity • Delay time: 1 days

Otherwise, once the tool is identified to be used, it goes for disassembly, and that is represented by a Delay block where the delay time is specified and set to one day with maximum capacity. Having maximum capacity delays based on the resources available after the first Seize block plays a role in painting a realistic representation of the real process. The "Disassembly" Delay block is detailed in Table 5.7 below.

Table 5.7: *"Disassembly" delay block.*

Block name	Functions	Properties
Disassembly	Delay	• Maximum capacity • Delay time: 3 days

The disassembly is followed by a SelectOutput5 block called "UsedSplit" in order to separate potential outcomes of the used tool of the disassembled tool. The reason for using SelectOutput5 instead of SelectOutput is because it has three possible outcomes. The SelectOutput5 is presented below with its probabilities based on the data collection, where the number of visits of each outcome was ratioed over the total amount of visits accounted for from the historical data obtained in Chapter 3. The probabilities are presented in Figure 5.11 below with 0.326 being for the replacement being needed, 0.404 being for the repair being needed, and 0.27 being for neither where the tool has no unforeseen issues.

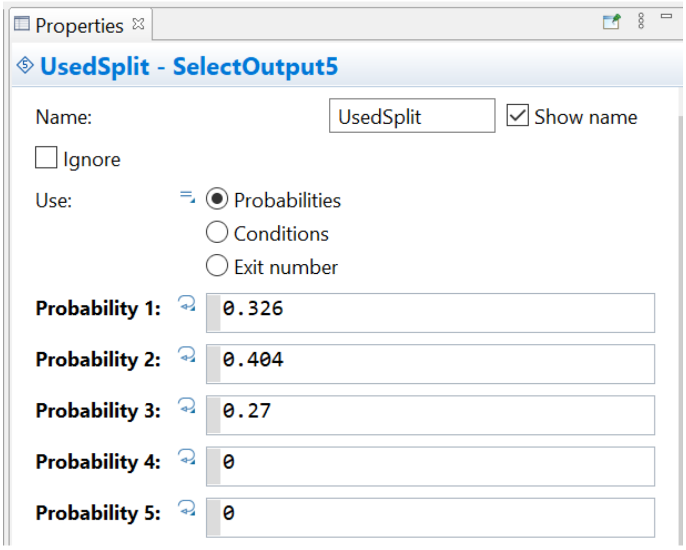


Figure 5.11: *UsedSplit SelectOutput5*

Taking the "NoIssuesTrack" first from the "UsedSplit", it consists of a Queue followed by a Delay in order to present the used maintenance process that includes standard part The Table 5.8 is presented below to show the parameters used for this track.

Table 5.8: *NoIssuesTrack blocks.*

NoIssuesTrack blocks	Functions	Properties
Qnorepair	Queue	• Maximum capacity • Queuing: FIFO
NoRepair	Delay	• Maximum capacity • Delay time: 1 days

The second potential track is the "RepairComponentTrack", and this represents the need to outsource repairs for failed components. This is done by adding a Release block to remove booked workshop workers from the tool and allowing the tool to not interfere with workshop capacity as it gets repaired. After the Release, there is a Queue and a Delay to perform the repairs. Once done, the tool is then linked back to a worker using the Seize block and rejoined into the main flow to be assembled and be sent out. The properties of this track are represented in the Table 5.9 below.

Table 5.9: *RepairComponentTrack blocks.*

RepairComponentTrack blocks	Functions	Properties
ExternalRepair	Release	• Release: All seized resources
QRepair	Queue	• Maximum capacity • Queuing: FIFO
Repair	Delay	• Maximum capacity • Delay time: 5 weeks
Seize6	Seize	• Resource set: "Worker_Pool" • Queue Capacity: 200

The third and final output from the "UsedSplit" is the "ReplaceTrack" and that is where the issues arose for the case company. To begin the track has a "replace" release function which releases the workers initially attained for this track. This is done to add the realistic logic into the model, where if there are stock shortages, the model would not keep the worker seized until the component is procured. The release "replace" in turn has its properties set to "Release: All seized resources" and is followed by a SelecOuput5 called "ComponentSplit" that separates each needing replacement component from the finalized critical components. The probabilities assigned within "UsedSplit" are the ratios of each component replacement over the total amount of component replacements accumulated over 2021 and 2022 for the case company, then converted into a percentage so as to have it be a probability. This is implemented as shown below in Figure 5.12

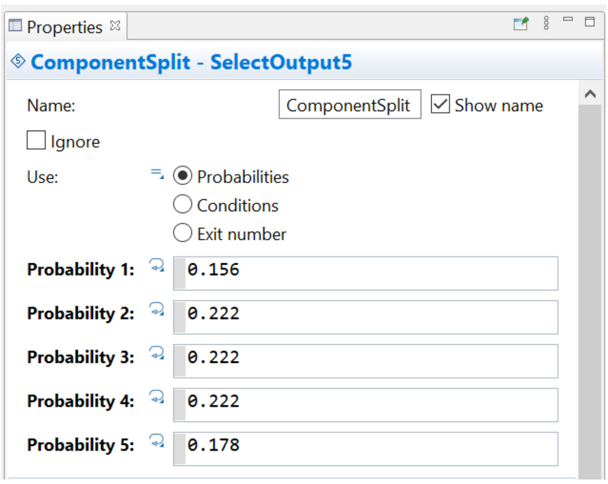


Figure 5.12: *ComponentSplit SelectOutput5*

For each of the probabilities, a defined set of discrete events exist, and to have a functioning inventory management discrete event flow, we need hold blocks to be activated when stock shortages occur. For whichever of the five components that needs replacement, there exists a hold block for it. For Comp. 1 that is “hold1”, for Comp. 2 it is “hold2”, for Comp. 3 it is “hold3”, for Comp. 4 it is “hold4”, and finally Comp. 5 has “hold5”. These act as blockages and are activated through a designated state chart for each.

In total, there are five different tracks stemming from the “ComponentSplit”, and all five tracks follow the same logic of component replacement. They all begin with a Queue which receives and accounts for all replacement demands needed by the used tool, and this is followed by a hold which blocks the replacement in case there are stock shortages. Once the component is identified to be on stock, the hold will not be activated, and there would be a seize block to attain a workshop worker for the replacement followed by a Delay for accounting time and inventory changes due to the replacement activity before the tool is rejoined back onto the main flow for assembly and checkout.

For better distinction, the five identified components in Chapter 3 were assigned to a corresponding replacement track. In other words, Comp. 1 follows the first track with “Qreplace1” Queue, Comp. 2 follows the second track with “Qreplace2” Queue, and so on till Comp. 5, which follows the fifth track with “Qreplace5” Queue. The properties of these five tracks of replacement are represented in the Table 5.10 below.

Table 5.10: *ReplaceTrack blocks.*

ReplaceTrack blocks	Functions	Properties	Actions and Explanations
• Qreplace1 • Qreplace2 • Qreplace3 • Qreplace4 • Qreplace5	Queue	• Capacity: 100 • Queuing: FIFO	
• hold1 • hold2 • hold3 • hold4 • hold5	Hold	• Mode: Manual (use block(), unblock()) • On enter: self.setBlocked(**true**);	
• Seize1 • Seize2 • Seize3 • Seize4 • Seize5	Seize	• Resource sets: “Worker_Pool” • Queue Capacity: 200	

Replace1	Delay	• Maximum capacity • Delay time: 1 day	On enter: SparePartsStock1=SparePartsStock1-1 This deducts one of the stock quantities for Comp. 1.
Replace2	Delay	• Maximum capacity • Delay time: 1 day	On enter: SparePartsStock2=SparePartsStock2-1 This deducts one of the stock quantities for Comp. 2.
Replace3	Delay	• Maximum capacity • Delay time: 1 day	On enter: SparePartsStock3=SparePartsStock3-1 This deducts one of the stock quantities for Comp. 3.
Replace4	Delay	• Maximum capacity • Delay time: 1 day	On enter: SparePartsStock4=SparePartsStock4-1 This deducts one of the stock quantities for Comp. 4.
Replace5	Delay	• Maximum capacity • Delay time: 1 day	On enter: SparePartsStock5=SparePartsStock5-1 This deducts one of the stock quantities for Comp. 5.

Once the tool is done with any of the previously discussed tracks following a used tool maintenance process, the tool is then ready for assembly. The tracks are all re-joined into the main process flow, and they are met with a Queue, followed by a Delay, and finally a Release block to free up the workshop workers for new jobs. Once the workers are returned to the "Worker_Pool", a Sink is used for tool exiting. The Table 5.11 below illustrates the properties of the checkout section of the process flow.

Table 5.11: *Assembly and Checkout blocks.*

Assembly/Checkout blocks	Functions	Properties
Assembly	Queue	• Maximum capacity • Queuing: FIFO
CheckOut	Delay	• Delay time: 2 days • Maximum capacity
release_Workers	Release	• Release: All seized resources (of any pool)

Having covered the discrete events flow process, it is important to support that with the necessary functions such as the Stock blocks, Parameters, and State charts within the "main" agent.

The Hold blocks discussed previously are all linked to their corresponding state charts. A visualization of the state charts is presented below in Figure 5.13, and the "hold1" Hold block state chart is highlighted and will be further explained.

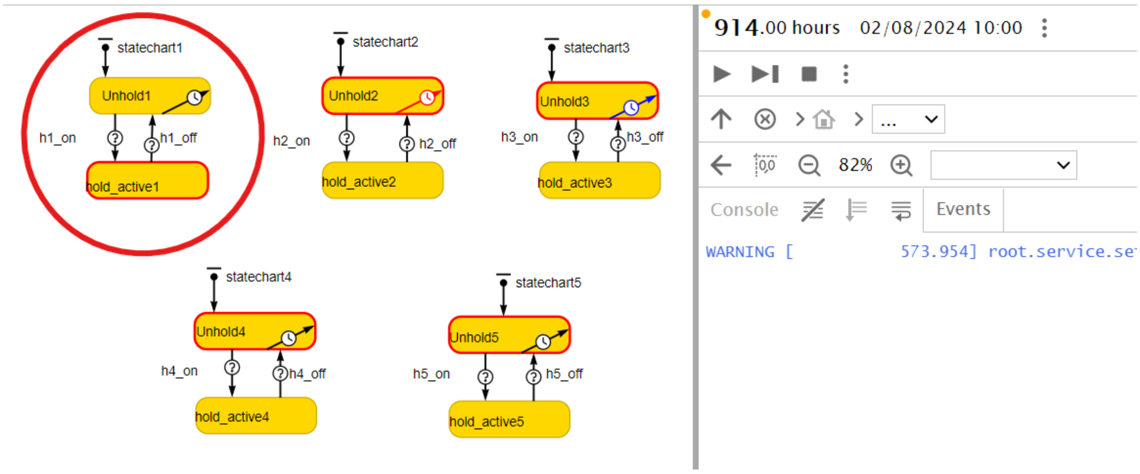


Figure 5.13: *Hold state charts*

The highlighted state chart follows the same exact logic as the rest, therefore, the replication of the same steps with modification of numbers to match each Hold block will result in the same output. So, only the highlighted one is detailed below in Table 5.12.

Table 5.12: *Hold1 Statechart properties.*

Name	Type	Properties and Explanation
statechart1	Statechart Entry Point	N/A
Unhold1	State	N/A
h1_on	Transition	• Triggered by: Condition • Condition: repairedstock1 < 1; • Action: hold1.setBlocked (true); Once the condition is met, the hold block is activated through the action.
hold_active1	State	N/A
h1_off	Transition	• Triggered by: Condition • Condition: repairedstock1 > 0; Once the condition is met, the hold block is released through going back to “Unhold1” state.

The Hold function keeps checking for when it needs to be activated using an internal transition within the state "Unhold1" where it remains open and unblocked until the "h1_on" condition is met. This is detailed within Figure 5.14 presented below.

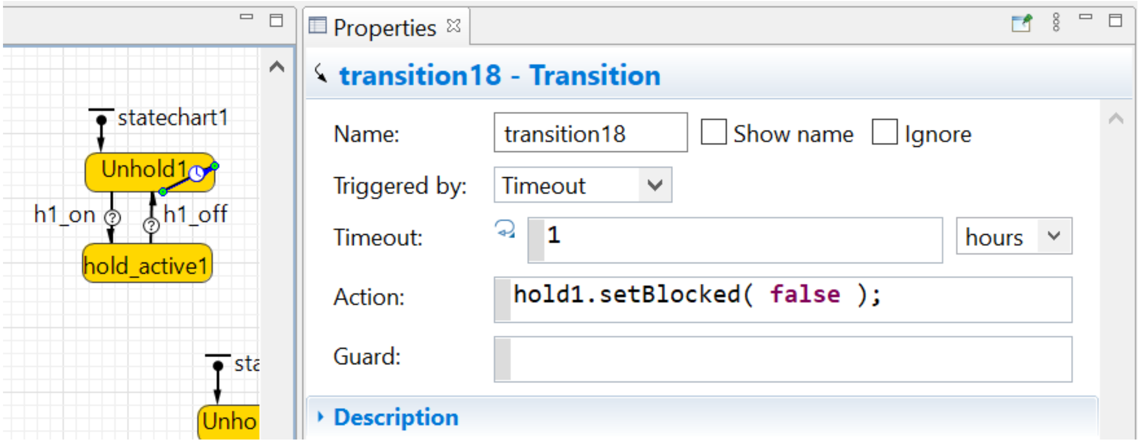


Figure 5.14: *Unhold1 internal transition*

The "main" agent extends to cover the stocks and parameters used to keep track of the inventory being utilized throughout the maintenance process flow. This is done by assigning a Stock to each of the components in this research, and two parameters. The first parameter is for the batch supplied to the stock, and the second parameter is for the re-ordering point of the batch to fill up the stock. These two parameters exist for each stock and are labeled by numbers, so "Batch1", "Reorder_point1" are for "SparePartsStock1" and they are all linked to Comp. 1. The rest follow the same logic and correspond to the remaining components. The Figure 5.15 below illustrates the used stocks and parameters.

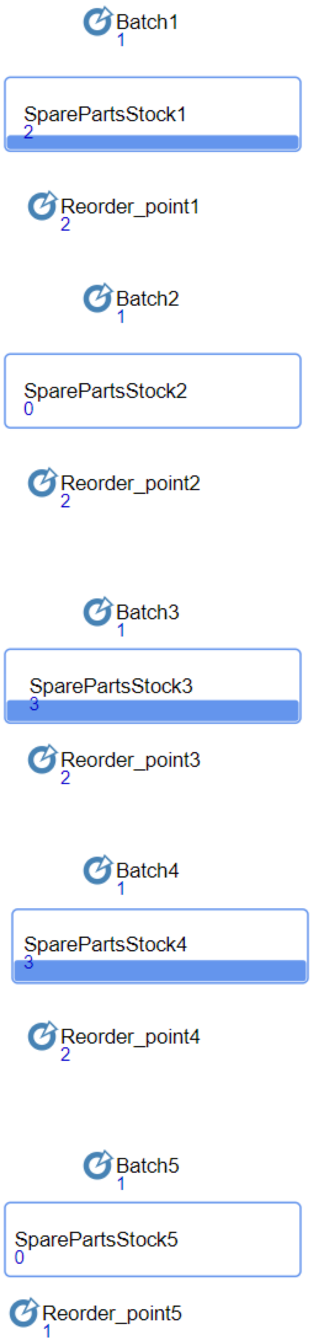


Figure 5.15: *Baseline model stocks*

The parameters used within this section were based upon the data collection in Chapter 3, and follow the current parameters utilized by the company. Table 5.13 below shows all properties within these parameters and stocks.

Table 5.13: *Baseline model stocks inputs.*

Name	Type	Properties
• Batch1 • Batch2 • Batch3 • Batch4 • Batch5	Parameter	• Type: double • Default value: 1
• Reorder_point1 • Reorder_point2 • Reorder_point3 • Reorder_point4	Parameter	• Type: double • Default value: 2
• Reorder_point5	Parameter	• Type: double • Default value: 1
• SparePartsStock1 • SparePartsStock2 • SparePartsStock3 • SparePartsStock4	Stock	• Initial value: 3
• SparePartsStock5	Stock	• Initial value: 1

Finally, the "main" agent includes five other agents as shown on the left side of Figure 5.5. The agents are responsible for the supply chain of the procured components from the best cost country. They are called "orderp1" for Comp. 1, "orderp2" for Comp. 2, "orderp3" for Comp. 3, "orderp4" for Comp. 4 and "orderp5" for Comp. 5.

By going inside one of these agents, each one contains a state chart and a set of discrete events which represent the supply chain process of these components. Taking "orderp1" in details as an example to give an understanding of how this process functions will further show the interconnections between the state chart and the discrete events within to end with the refilling of "SparePartsStock1" Stock as presented in Figure 5.16 below.

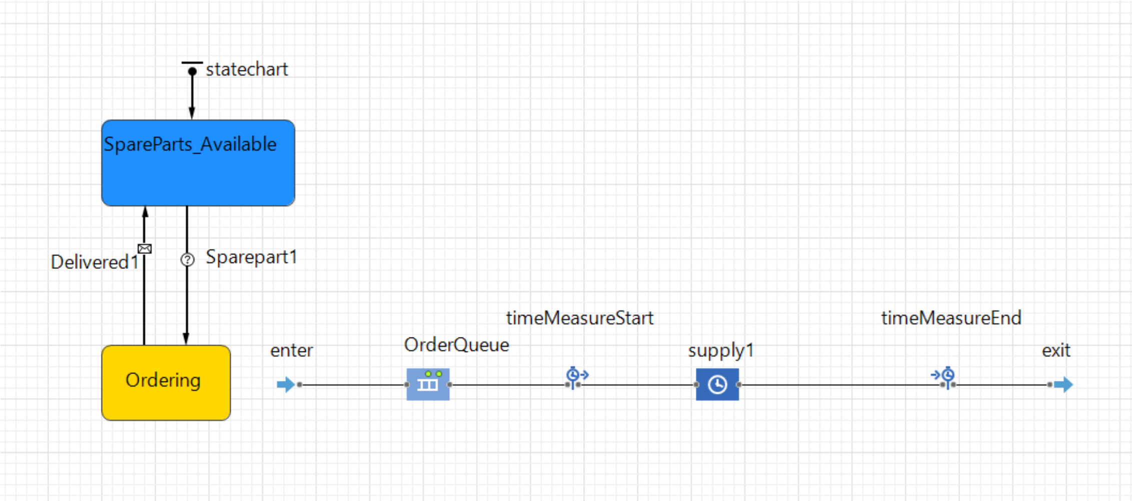


Figure 5.16: *“orderp1” agent process flow*

The overview above consists of a state chart that triggers a supply order that is based on the stock falling below the re-order point threshold. This takes the order into the “enter” Enter block initiating the discrete events flow. Along the discrete events flow, there is a TimeMeasureEnd plotted in order to keep track that the supply is going correctly following the tool specialist’s inputs from the case company. Below is Table 5.14 breaking down each discrete event block, along with the state chart states and transitions’ properties.

Table 5.14: *“orderp1” agent blocks properties.*

Name	Type	Properties and Explanation
enter	Enter	
OrderQueue	Queue	• Maximum capacity • Queuing: FIFO
timeMeasureStart	TimeMeasureStart	
supply1	Delay	• Maximum capacity • Delay time: 365 days • On exit: send("done1",agent);
timeMeasureEnd	TimeMeasureEnd	
exit	Exit	
statechart	Statechart Entry Point	
SpareParts_Available	State	

Sparepart1	Transition	• Triggered by: Condition • Condition: main.SparePartsStock1 <= main.Reorder_point1 • Action: main.hold1.setBlocked(true); enter.take(this); This transition activates when the re-order point is reached and takes the agent into the "enter" Enter block while activating the Hold block.
Ordering	State	
Delivered1	Transition	• Triggered by: Message • Message: "done1" • Action: main.hold1.setBlocked(false); main.SparePartsStock1 += main.Batch1; This transition activates once the "supply1" Delay is done where it adds the "Batch1" value to "SparePartsStock1" Stock and deactivates the Hold block.

The parameters of each agent, such as "orderp1" correspond to refilling the component's dedicated stock, being "SparePartsStock1". This in turn means that the replication of these steps within the other agents will give the same output through modifying the Stock, Batch and Hold blocks names within the properties of the blocks.

5.9 Enhanced Model

In order to apply the mapped conceptual enhanced system discussed previously within AnyLogic, some structural modifications within the baseline model were applied. It was modified to implement the repaired-parts cycle system, which involved replacing faulty components from stock and returning the repaired part back to stock for future use. The modified model aimed to streamline the maintenance process flow, reduce lead times, and minimize procurement expenditures on the long run through future proofing existing components. The model incorporated the demand forecasts and inventory management techniques discussed in the literature review to ensure its effectiveness and relevance to the case company's operations.

The model structure was built on the baseline model but with some modifications within the "main" agent which represented the enhanced process flow of maintenance, and this is shown in Figure 5.17 below. The maintained tool would follow the same inputs "source" and "arrivalSchedule", seizing of workers "Seize_Workers", identification procedure "UsedorUnused", unused maintenance flow "NoIssuesTrack", and checkout process from "CheckoutTimeStart" until the "sink" exit. Agents "orderp1", "orderp2", "orderp3", "orderp4", and "orderp5" were used as is from the baseline model. The main differences only occurred within the used maintenance procedures "ReplaceTrack", Stocks blocks, and State charts.

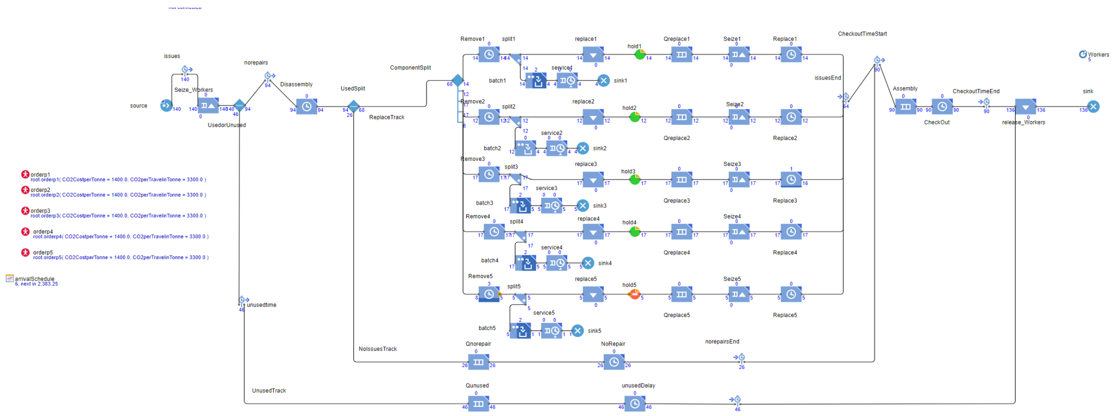


Figure 5.17: *Enhanced model maintenance process flow*

To begin with the model structure differences, the first change is witnessed in the "UsedSplit" SelectOutput. This is different from the SelectOutput5 used in the baseline model due to the removal of the "RepairComponentTrack" process flow. This meant that there are only two possible outputs now, either it has repairs, or has no issues and follows the "NoIssuesTrack". The probabilities were changed to 0.73 to suit this structural modification meaning there is a 73% probability the tool encounters at least one component with issues. This is presented below in Figure 5.18 stemming from the historical maintenance data collection in Chapter 3.

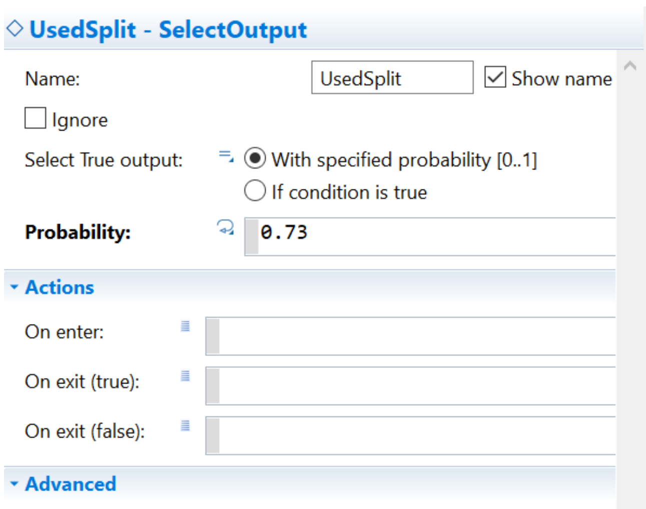


Figure 5.18: *Enhanced model "UsedSplit"*

Once the tool is identified to be used, it is then taken to the "ComponentSplit" SelectOutput5 which is the same block used within the baseline model. However, from that point, there are a lot of changes within each of the five tracks with component issues. With the new structural change of including repaired-path cycle, the tool is not to be affected by component failures. In other words, whether the failure is repairable or not, the tool will have the component replaced, and the component is serviced and returned to stock.

The flow begins with a Delay for removing the faulty component, then a Split block which separates the tool from the faulty component. This is done so the tool can have its component replaced while the originally failed component is being repaired. Once the component has been separated by the Split block, it is taken into a Batch block. This is done based on the tool specialist's interview at the case company, where the business is looking for maintenance cost reductions through bulk repairs. Once the bulk size specified is reached, the tool goes through a Service block which has a Delay time within which accounts for the proposed future proofing of components. This is finally followed by a Sink block once the services are performed and the repaired components are returned to stock. For instance, Comp. 1 now has "scrapper1" Stock to scrap irreparable components, and "repairedstock1" being the main utilized stock rather than "SparePartStock1" which was used in the baseline model. The "SparePart-Stock1" Stock is still used, but merely as a backup stock that is used in case shortages within the "repairedstock1" exist.

On the other hand, the tool once separated goes through a Release block which releases the worker currently assigned to it in case there are stock shortages. This means the worker is not obligated to wait for the stock availability in order to work, but can alternatively be busy with other tools in the meanwhile. Following that, a Hold block exists to stop the flow when no stock is available at that moment. In case the Hold is inactive, a Queue is placed to take in tools needing component replacements, and is followed by a new Seize block. This Seize block brings back a free workshop worker in order to replace the component now on stock through a Delay block for replacement. Once done, the tool is rejoined on back on the main process flow in order to be assembled and checkout.

This way, the tool maintenance flow is independent of component failures and can be streamlined drastically. To better illustrate the changes, Table 5.15 below is created detailing the first track starting with "Replace1" which similar to the baseline model, represents Comp. 1.

Table 5.15: *Enhanced model ReplaceTrack blocks.*

ReplaceTrack blocks	Functions	Properties	Actions and Explanations
Remove1	Delay	• Delay time: 1 hour	
Split1	Split	• Number of copies: 1	
batch1	Batch	• Batch size: 3	
service1	Service	• Delay time: 5 weeks	**On at exit**: repairedstock1=repairedstock1+3; scrapper1 = scrapper1 + 3; //This supplies the repaired stock with the repaired components and adds the batch size to the scrap counter.
sink1	Sink		
replace1	Release	• Release: All seized resources (of any pool)	
hold1	Hold	• Mode: Manual (use block(), unblock()) • On enter: self.setBlocked(**true**);	
Qreplace1	Queue	• Capacity: 100 • Queuing: FIFO	
Seize1	Seize	• Resource sets: "Worker_Pool" • Queue Capacity: 200	
Replace1	Delay	• Maximum capacity • Delay time: 1 day	**On enter:** repairedstock1=repairedstock1-1 //This deducts one of the repaired stock quantities for Comp. 1 being used.

The remaining tracks out of "ComponentSplit" follow the same exact logic, but each reflects its corresponding component. For example, the second track starting with "Remove2" represents Comp. 2 and so forth. This indicates that the replication of these steps, alongside the modification of the Stock names will result in a similar output for all remaining components.

Moving onto the Stock blocks and State charts, the same Hold state charts used in Figure 5.13 were applied within the enhanced model. However, two new Stock blocks were created to account for repaired components as a first defense line when failures occur, and another to account for the scrapping of tools that have reached their product life cycle and cannot be further repaired. The Figure 5.19 below visualizes the new Stock blocks implemented and the new state charts used for these Stock blocks.

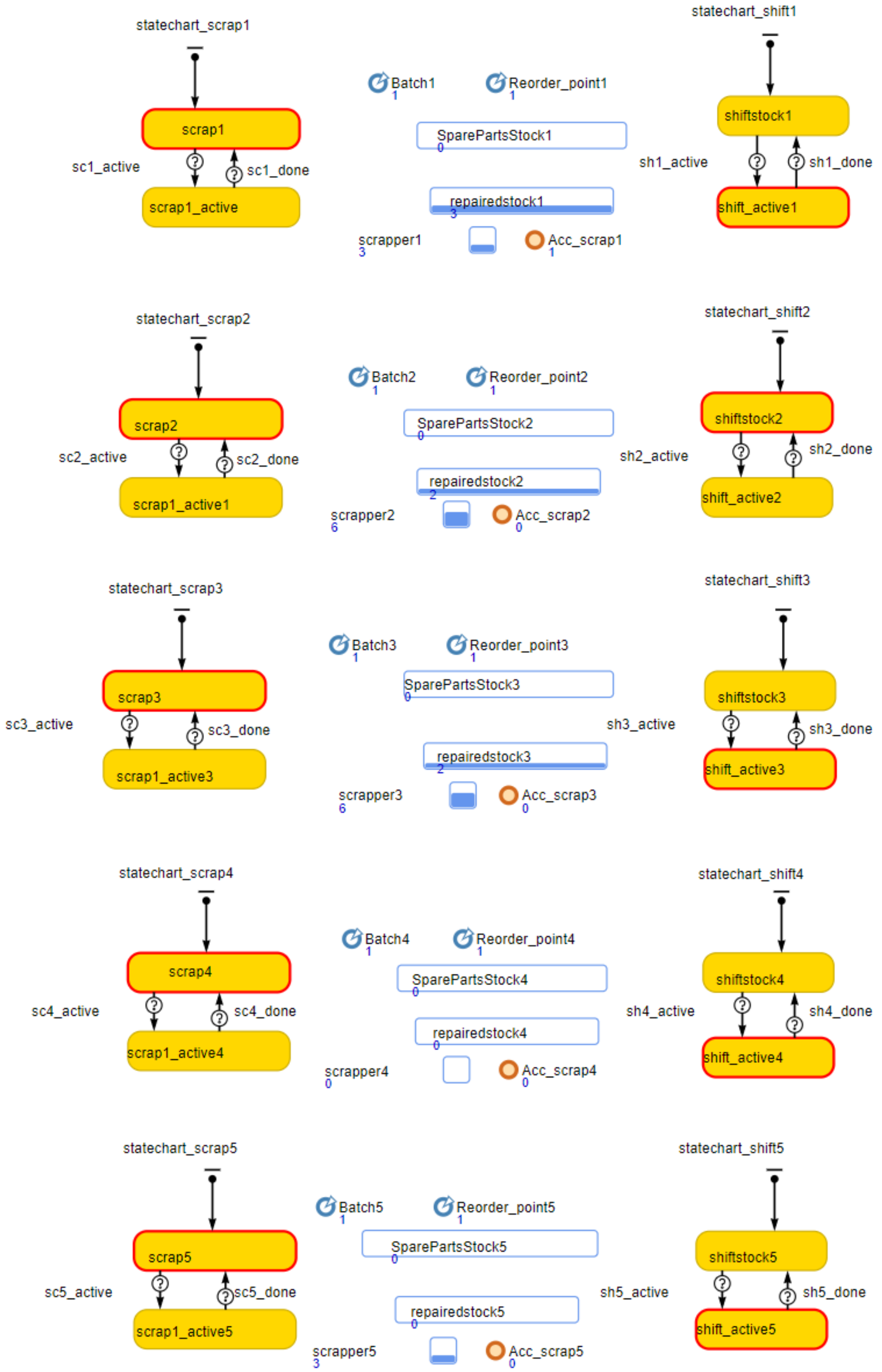


Figure 5.19: *Enhanced model stock structures*

The figure displays three Stock Blocks and two new state charts utilized for each component. Taking Comp. 1 in details for example, the state chart “statechart_ scrap1” is used to scrap irreparable Comp. 1 parts, and another “statechart_shift1” is used to shift inventory stocks between the “SparePartStock1” and the “repairedstock1” Stock blocks when needed for replacements. Moreover, “scrapper1” Stock is added to count all repaired components and initiate the scrapping when needed. Finally, a new variable is added to accumulate scraps “Acc_scrap1” and acts as a counter to visualize the number of scraps by the end of the model time. A detailed overview on properties and inputs of the taken example is provided in Table 5.16.

Table 5.16: *Enhanced model Comp. 1 Inventory management system properties.*

Name	Type	Properties and Explanation
Acc_scrap1	Parameter	• Type: double • Initial value: 0
Statechart_scrap1	Statechart Entry Point	N/A
scrap1	State	N/A
sc1_active	Transition	• Triggered by: Condition • Condition: scrapper1 = = 9;
scrap1_active	State	N/A
sc1_done	Transition	• Triggered by: Condition • Condition: scrapper1 == 9; • Action: scrapper1 = 0; repairedstock1 = repairedstock1-1; Acc_scrap1=Acc_scrap1+1; Once the condition is met, the scrapper counter is repeated from zero and a scrap is counted.
statechart_shift1	Statechart Entry Point	N/A
shiftstock1	State	N/A
sh1_active	Transition	• Triggered by: Condition • Condition: repairedstock1 < 1;
shift_active1	State	N/A
sh1_done	Transition	• Triggered by: Condition • Condition: SparePartsStock1 > 0; Action: SparePartsStock1 = SparePartsStock1-1; repairedstock1 = repairedstock1 + 1; Once the condition is met, the stock is shifted from “SparePartsStock1” to “repairedstock1” to meet replacement demands.

The remaining components have the same exact inventory management structure and follow the same logic. So, applying the same structure to the remaining components and modifying the names of the Stock blocks, Parameters, and Variable will result in the same output.

Each of the components has a dedicated batching stock such as "Batch1" for Comp. 1 which is responsible for the re-order quantity when needed. Moreover, each component has a dedicated repaired parts stock post servicing faulty components that gets utilized on demand for other needing tools, such as "repairedstock1" for Comp. 1. However, if no repaired components are on stock, the tool is able to utilize new build stocks such as "SparePartsStock1" for Comp. 1. Once the new build stock drops below a threshold specified as a re-order point, such as "Reorder_point1" for Comp. 1, a new supply order is placed similar to the baseline model. Finally, a separate stock such as "scrapper1" for Comp. 1 keeps count of the amount of repaired tools to account for needed scraps over time, as a way of keeping the model as realistic and reflective of the real workshop as possible. All the inputs are provided below in Table 5.17.

Table 5.17: *Enhanced model stocks inputs.*

Name	**Type**	**Properties**
• repairedstock1 • repairedstock2 • repairedstock3 • repairedstock4 • repairedstock5	Stock	Initial value: 0
• scrapper1 • scrapper2 • scrapper3 • scrapper4 • scrapper5	Stock	Initial value: 0
• Batch1 • Batch2 • Batch3 • Batch4 • Batch5	Parameter	• Type: double • Default value: 1

• Reorder_point1 • Reorder_point2 • Reorder_point3 • Reorder_point4	Parameter	• Type: double • Default value: 2
• Reorder_point5	Parameter	• Type: double • Default value: 1
• SparePartsStock1 • SparePartsStock2 • SparePartsStock3 • SparePartsStock4	Stock	• Initial value: 3
• SparePartsStock5	Stock	• Initial value: 1

5.10 Financial parameters of interest

The financial analysis of the model for the problem under discussion requires considering two main factors. The first being the current financial burden associated with elongated lead times and high maintenance costs, and the potential financial implications of implementing the proposed repaired-path cycle solution.

Currently, the case company incurs significant costs due to the inefficient inventory management system. The prolonged lead times for tool maintenance not only increase the operational costs but also affect revenue generation. Offshore operational delays translate into lost opportunities and financial losses due to missed contracts. Additionally, high maintenance costs, especially when components need to be repaired or replaced, further strain the financial resources of the company. These costs are a direct result of the current operational inefficiencies, and they highlight the urgency for a restoration of the inventory management system.

The proposed solution, being the integration of a repair path cycle into the maintenance process, necessitates an upfront investment. This investment includes setting up the repair cycle system, and implementing a bulk repair strategy. However, this cost is likely to be offset by the potential savings due to a reduction in lead time, a decrease in the rate of failures, and a streamlined maintenance process. While exact cost calculations will require specific data regarding the investment required and the expected savings, the overall trend suggests a positive net present value (NPV) for this solution in the long run.

Specific cost figures and financial plots would be needed to validate these assumptions and provide a detailed cost-benefit overview. To do that, financial stocks were added to account for the repairs and procurement costs.

To account for revenues and costs, a set of financial figures were taken from the case company with a multiplication factor due to the confidentiality. The values are separated in three categories, the revenue from sending tools back offshore, the average cost of future proofing the top five selected component repairs, and the cost of procurement from the data collection in Chapter 4. In Table 5.18 below are the two advised average repair costs used within the model for financial evaluating purposes.

Table 5.18: *Financial parameters.*

Tool output revenue	Bulk repair cost per component	Single repair cost per component
90,000 NOK	20,000 NOK	30,000 NOK

In order to implement these revenues and costs within the model, Output blocks were implemented in both the baseline and the enhanced models. These Output blocks were "Revenue" for the tool output revenue calculation, "repairCost" for the accounting of tool repairs, and "ProcurementCost" for the sourcing of new build components when necessary. The Figure 5.20 below shows the structure of the financial parameters' calculations.

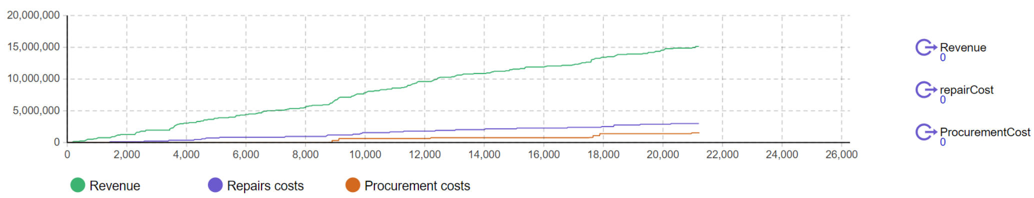


Figure 5.20: *Financial parameters structure*

In order to better illustrate these parameters, and the way they operate, the Table 5.19 below details each equation used within the baseline and the enhanced models.

Table 5.19: *Financial blocks properties*

Block Name	Function	Properties
Revenue	Output	Value: sink.in.count()*90000
repairCost (baseline model)	Output	Value: Repair.out.count()*30000
repairCost (enhanced model)	Output	Value: service1.out.count()*60000 +service2.out.count()*60000 +service3.out.count()*60000 +service4.out.count()*60000 +service5.out.count()*60000
ProcurementCost	Output	Value: orderp1.exit.in.count()*260000 + orderp2.exit.in.count()*310000 + orderp3.exit.in.count()*134000 + orderp4.exit.in.count()*272000 + orderp5.exit.in.count()*340000

5.11 Verification and validation of the inventory management model

The developed inventory enhancement model needed to be critically tested for its accuracy and functionality. This process was guided by a series of stages aiming to ensure that the model is not only theoretically sound but also practically effective in minimizing maintenance time and cost while meeting operational demands.

First, historical data was verified from the case company, and that included demand, lead times, frequency and duration of maintenance, and the procurement costs of spare parts. This information laid the groundwork for the calibration of the model parameters, which included selecting appropriate methods of demand forecasting, inventory policies, and safety stock levels.

Next, the tool specialist from the case company provided their expertise during this verification stage, contributing to the model's practical accuracy. The comments provided are as follows:

- Seize and release blocks the placement within the AnyLogic model structure for the workshop workers to reflect the exact periods of worker allocation in order to accurately replicate the real process.
- Batching of three components for the repairing process of the repair-path cycle before sending them due to the cost savings on repairs.
- Logistical delay time inputs and probabilities for the different maintenance paths were verified to reflect an accurate representation of the workshop distributions.

All the previously mentioned points were taken into account, and consequently, the model was revised. Following this, the validity of the inventory model was verified through several simulation runs with varying inputs, with outcomes checked for reliability and consistency.

This cooperative process involved both academic supervisors and the tool specialist from the case company, ensuring a comprehensive validation of the model's inputs. These simulations served to evaluate the model's effect on maintenance times and costs by varying the inputs.

The inventory enhancement model can be further integrated within the company's fleet in the future for its final evaluation and validation, and the model's performance can be closely monitored using the established KPIs to ensure that it continuously meets the needed operational objectives effectively.

Chapter 6

Results & Discussion

The results of the study are expected to contribute to the broader field of inventory management in the oil and gas industry, offering practical implications for practitioners and decision-makers.

6.1 Results and Discussion Outline

This chapter offers a comprehensive exploration and discussion of the results gathered from the comparative analysis between the baseline and enhanced models in the context of a spare parts inventory management system built within them. The results were evaluated using a range of performance metrics such as the maintenance lead times, workforce efficiency, and financial aspects all to provide invaluable insights into the effectiveness of the incorporated repair-path cycle. Both models used similar demand data sources, and initial inventory stock inputs. This helped establish a common basis of comparison between both maintenance process and inventory management approaches.

6.2 Lead Time Assessment

An initial comparative evaluation of lead times yielded a noteworthy decrease in the average lead time within the improved model. The mean lead time for the improved model was a mere 22% of the original, indicating a significant boost in the promptness of tool dispatch from the workshop. This reduction in lead time is associated with the introduction of the repair-path cycle, accelerating component replacements and repairs.

In order to better understand how these differences were analyzed, it is critical to begin with the baseline model which has almost 20% of the tools falling between the range 0 and 500 hours, while approximately 75% of the tools falling just short of the 1000 hours mark. Only few abnormalities were noticed on three short spikes on the right side of Figure 6.1 exceeding 4500 hours and demonstrating a six-month delay. However, when the model simulated all three years set for the model time, an average of 888.65 hours per tool was the lead time for tools experiencing at least one issue, has it been a repair or a replacement. This further showed the inefficiency of the currently implemented process flow of maintenance and how that holds the tool captive until the component is either found new on stock for replacement or has been repaired and ready to be assembled. The Figure 6.1 below visually represents all these findings and illustrates the percentage of tools on the y-axis over the accumulated lead times on the x-axis.

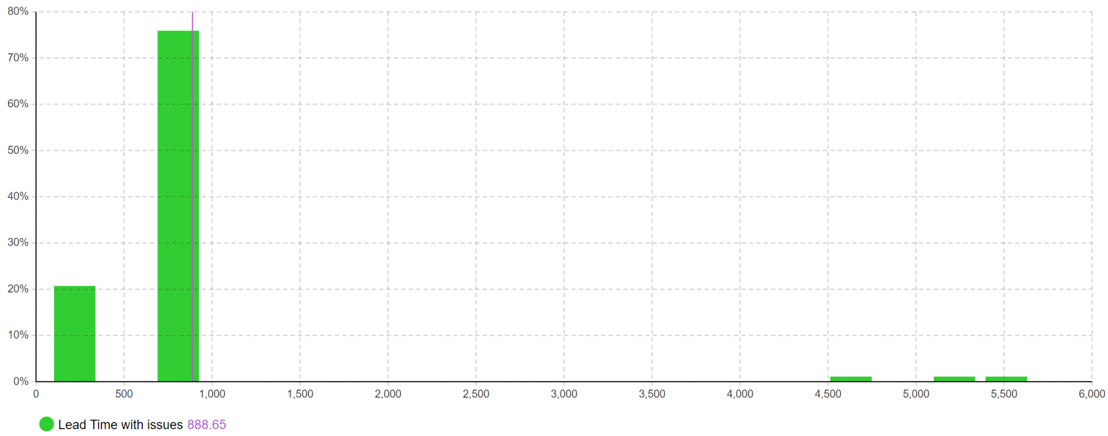


Figure 6.1: *Baseline model lead times of tools with issues*

As for the enhanced model, the lead times showed a lot of differences. This is majorly due to the fact that the tool detaches from the failed component. It is rational to assume the positive effect of it, but in no way was this the best possible achieved result due to the lack of optimization within the inventory stock inputs. Once the model was run through all three years, there was a clear shift in the lead time peaks where now over 90% of the tools had a lead time between 0 and 500 hours with just around 5% over 500 hours and a negligible range of abnormal cases witnessing 3000 hours of lead time and others reaching 5000 hours seen on the right side of the histogram Figure 6.2 below. However, as mentioned previously, these were the result of the lack of stock optimization and were not enough to discredit the major improvements resulted from the enhancement of the inventory management process flow. This is backed by the great reduction in lead times averaging 193.09 hours for tools that experienced at least one critical component issue.

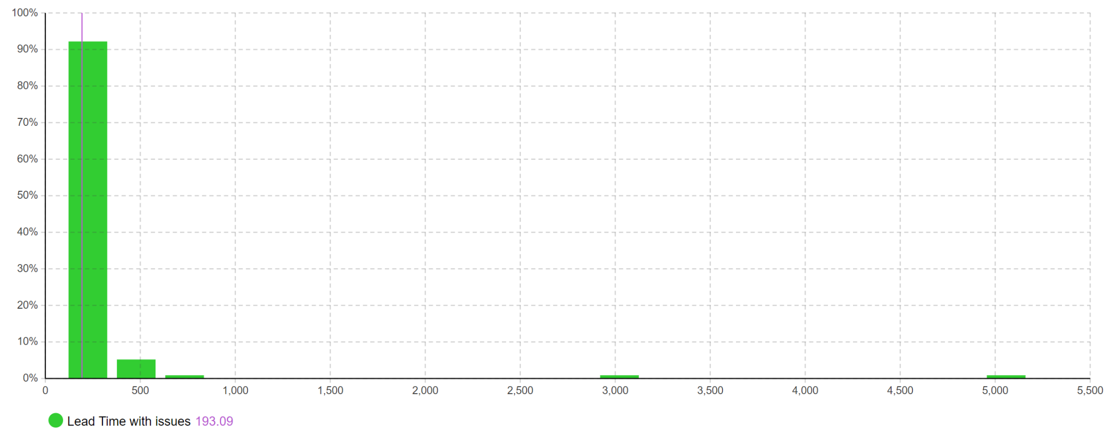
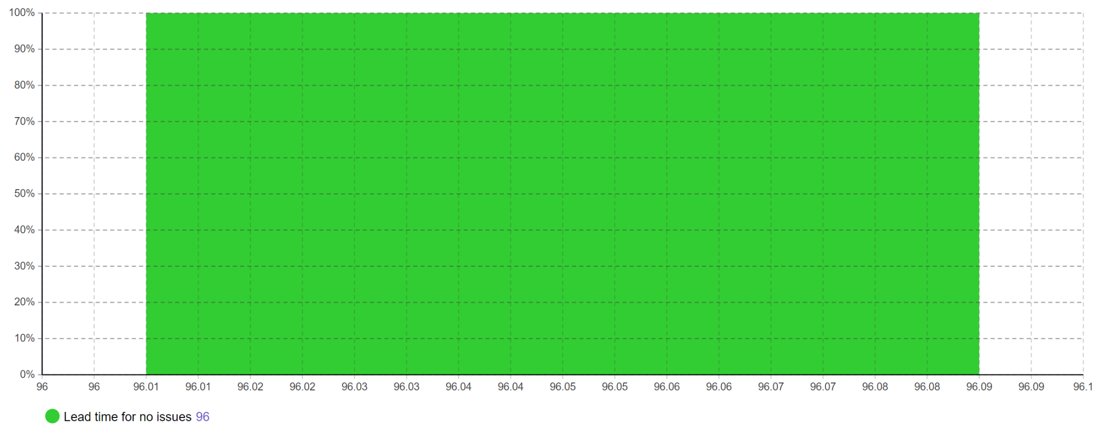
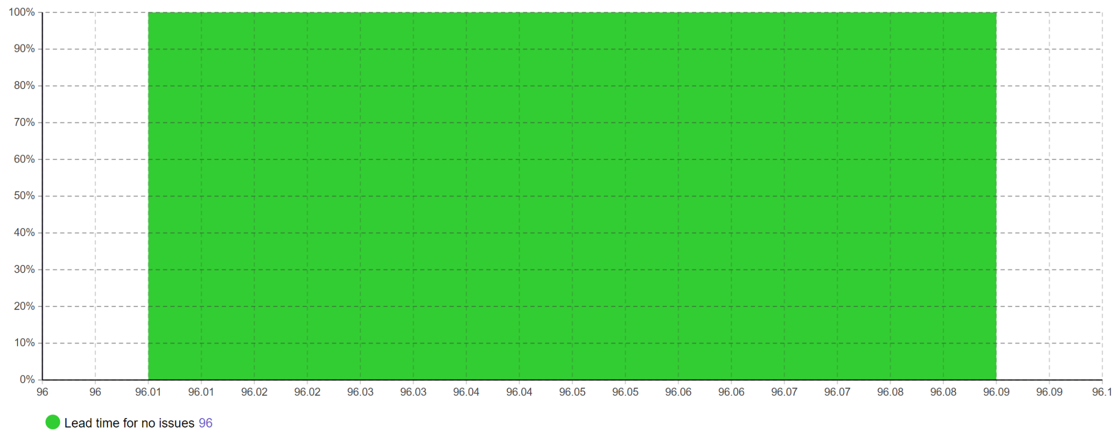


Figure 6.2: *Enhanced model lead times of tools with issues*

The enhanced model achieved congruent lead times to the baseline model in instances free of complications, suggesting that the repair-path cycle did not produce unnecessary delays or difficulties in the maintenance process. It implies through the 2 histograms, Figure 6.3a being the baseline model and Figure 6.3b being the enhanced model in Figure 6.3 below, that the introduction of the repair-path cycle did not detrimentally influence the maintenance procedures for tools not requiring component repairs or replacements.



(a) Baseline model lead times of tools with no issues



(b) Enhanced model lead times of tools with no issues

Figure 6.3: *Baseline and enhanced models lead times of tools with no issues*

6.3 Worker Utilization Analysis

The examination of worker utilization charts demonstrated a notable improvement within the enhanced model. Worker utilization surged from 0.73 in the baseline model to an impressive 1.58 in the enhanced model. This indicated a more efficient deployment of the workforce, as the repair-path cycle allowed for seamless maintenance activities progression and minimized the idle time for workers. This improvement in worker utilization is a critical contributor to the overall improved performance of the system and will be discussed in detail within this section.

To gain a comprehensive understanding of the system's existing conditions, a time plot was generated and illustrated in Figure 6.4a. This graphic explains the individual worker utilization rates over the span of a three-year model run, plotted on an hourly basis along the x-axis. The data unveiled an unexpected pattern of high worker utilization abruptly plummeting to zero, periods in which all workers were idle.

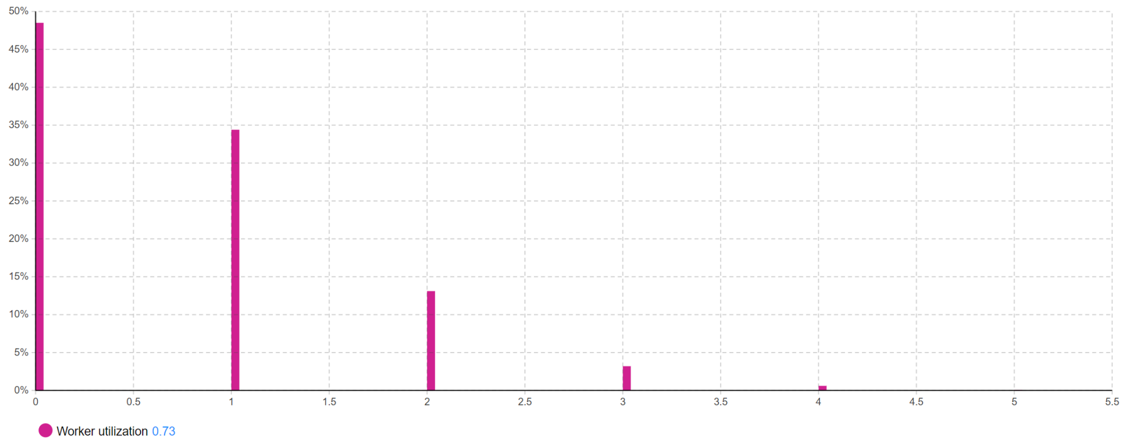
In addition, it was observed that a significant proportion of worker utilization was clustered between the zero to two range, indicating that frequently only one or two workers were engaged. Comparatively, instances, where all workers were put to work, were uncommon and relatively few, pointing out the inefficiencies in the case company's deployment of workers.

Nevertheless, the time plot did not provide detailed frequency data for each of these worker utilization levels. So, to address this, a histogram was introduced to provide a more in-depth breakdown of the frequency of each worker utilization level over the evaluated period.

Figure 6.4b showcases a histogram that compellingly illustrates the substantial potential for boosting productivity. This graph outlines the worker utilization patterns in the initial system, providing a baseline against which improvements can be measured. It reveals that the workers were idle nearly 50% of the time during the three-year period, signifying predominant inefficiencies. This extended idleness could be attributed to lengthy repair delays or periods of inventory shortage, which resulted in workers having no tasks to perform.

Such a high degree of worker idle time underscores the inefficacy of the currently established process flow and strongly emphasizes the importance and necessity of the research at hand. This study aims to explore potential remedies for these lapses, highlighting opportunities to make the system more efficient and productive. The histogram also showed the highest peak of workers utilized being at one worker at almost 35% of the time, while two workers deployment only happened for just under 15% of the time. Going further to the right-hand side of the histogram, lower peak times could be observed for three to five workers' utilization, accumulating under 10% of the total run time. Finally, the overall mean was found to be 0.73 meaning the highest range of deployment fell between idle and one worker showing how only one worker was depended on mostly.

(a) Worker utilization time plot



(b) Worker utilization histogram

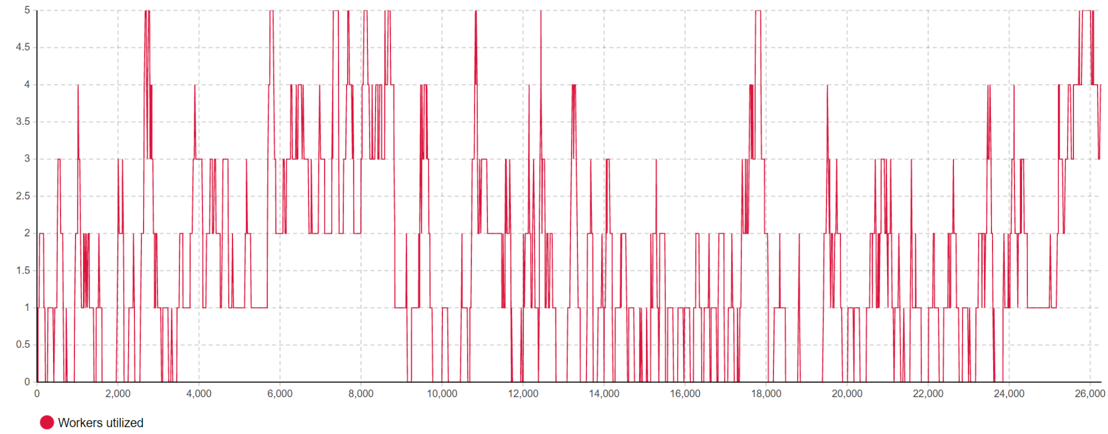
Figure 6.4: *Baseline model overview of worker utilization during model run time*

As for the enhanced model workflow, it detached the tool from the failed component and sends it for repair, and once repaired, it got returned to the repaired stock. This process ensured a smoother flow of maintenance activities, allowing the workers to maintain a consistent work rate rather than experiencing downtime due to waiting for repair tasks, and improving the efficiency of the system.

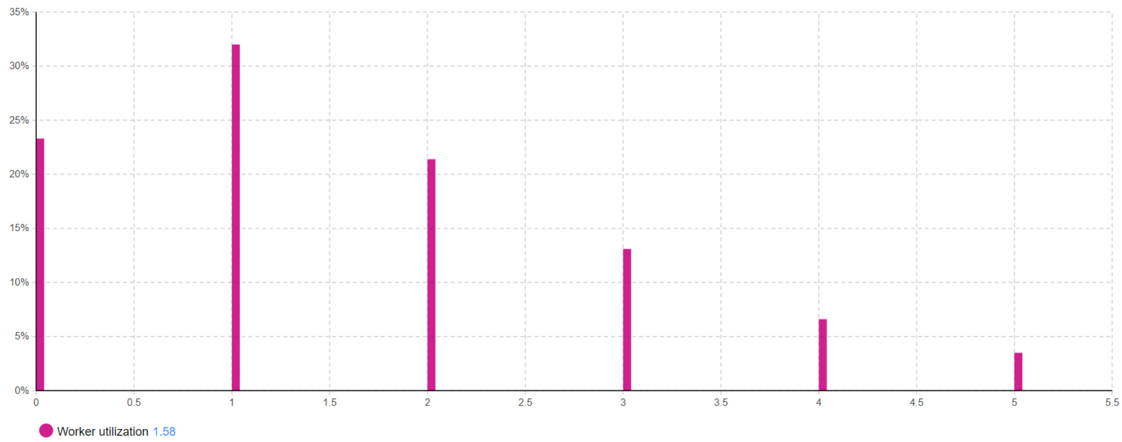
To demonstrate this, a time plot depicted in Figure 6.5a gave an insightful visualization of the worker utilization for maintenance tasks during the course of the model run time. It highlighted how the saturated frequency of workers utilized was now distributed between the range one to three workers operating simultaneously rather than just two of them as seen in the baseline model for the majority of the model run time. Furthermore, it uncovered moments of peak demand, during which all five workers were concurrently deployed due to high tool requirements. However, the chart fell short of specifying precise percentages of worker utilization. So, a histogram was incorporated in Figure 6.5b to elaborate on each worker's engagement frequencies.

The histogram demonstrated the workers' idle time vast reductions to less than that 25% of the total time, while over 30% of the time only one worker was engaged. Additionally, more than 20% of the time saw a simultaneous utilization of two workers. Concurrent requirement for three workers was observed during roughly 12% of the total time. The need for four workers was limited to about 7% of the three-year run time, and a mere 4% of the time necessitated the employment of all five workers simultaneously. All in all, an average of 1.58 workers utilization was obtained, demonstrating that between one and two workers were mostly needed.

This data offers the company valuable insights over the three-year period, where only around 4% of the time required the deployment of five workers simultaneously post enhancement. Hence, it suggests that the majority of the lead time reduction is contingent on the utilization of just four workers. This further highlights the possibility for additional cost savings in maintenance by trialing the model with fewer workers and comparing the impacts on lead times against the financial benefits of reduced wages.



(a) Worker utilization time plot



(b) Worker utilization histogram

Figure 6.5: *Enhanced model overview of worker utilization during model run time*

In conclusion, the notable increase in worker utilization as a result of the repair-path cycle implementation demonstrates the effectiveness of this new process in improving the productivity and efficiency of the inventory management system. However, it also underlines the need for continuous monitoring and adjustments to maintain an efficient work environment for the workshop workers.

6.4 Crowding Analysis

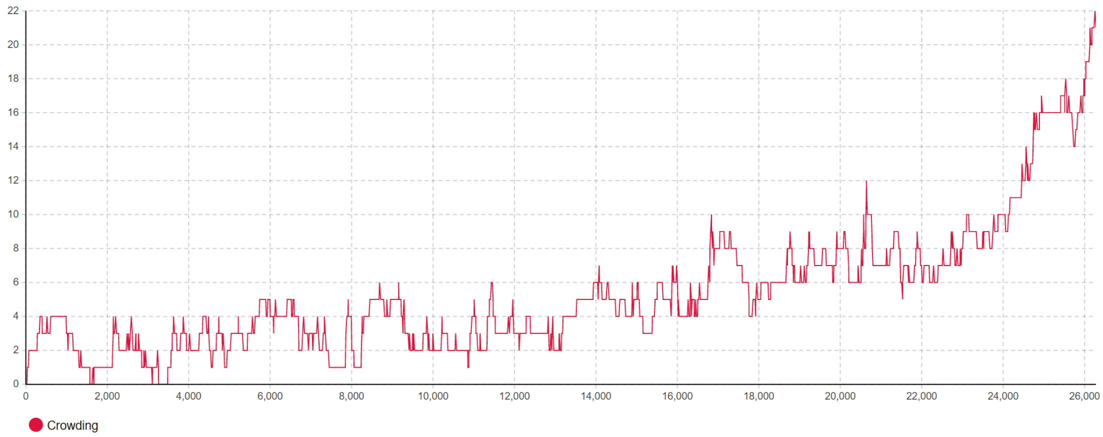
An analysis of the crowding time plots and histograms revealed a clear contrast between the baseline and the enhanced model. The initial model displayed escalated crowding levels by the end of the model time, implying an extended accumulation of tools in the workshop. Conversely, the advanced model indicated reduced crowding levels, suggestive of a more streamlined maintenance process and fewer bottlenecks. The implementation of the repair-path cycle played a pivotal role in curtailing tool waiting times and expediting the maintenance process. The crowding effect can be crucial when taking into consideration the ergonomics and stress levels caused by it on the workshop employees.

Frankly, seeing a continuously high number of tools in the workshop being delayed due to the current repair process will ultimately push the workers to expedite disassembles and assemblies. That in turn will lead to higher injury risks, and lower overall quality of maintenance in order to meet the operational demands on time.

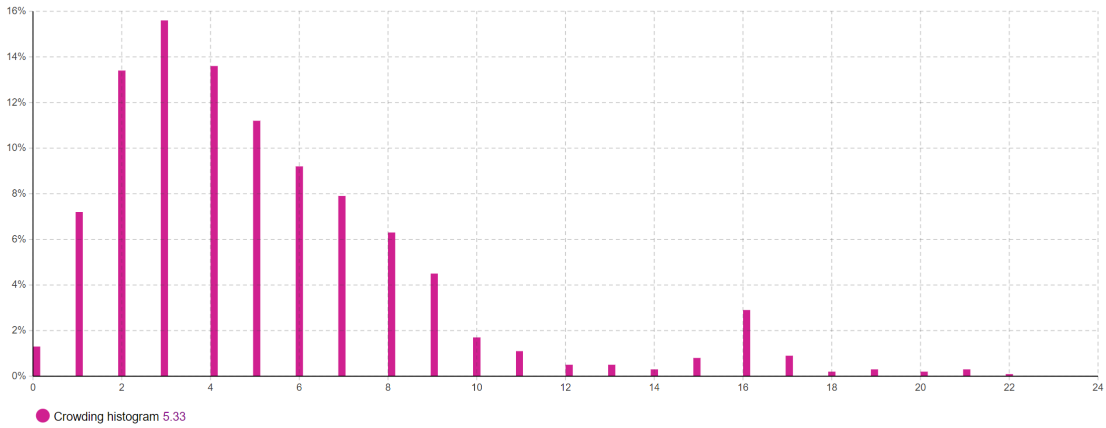
Through analyzing the baseline model time plot in Figure 6.6a, it is clear that for the first year of the model, the crowding frequencies were more or less stable under a controlled pattern, peaking at six tools. As the model run time progressed, there was a slight increase in crowded tools peaking once at 10 tools within the second year. However, an alarming surge in the crowded tools was evident in the third year as the delays accumulated due to stock shortages and repairs. This caused the third year to be the worst, peaking at 22 crowded tools and calling for a change before such drastic deterioration and loss of control occurs.

In order to detail the amount of tool crowding occurring at once, a histogram is implemented in Figure 6.6b. It showed approximately 60% of the model run time having five or less tools at once within the workshop, representing a low amount to no crowding at all and upright control. However, the remaining 40% of time saw six or more tools in the workshop creating a backlog that kept accumulating over the latter years and raising the need for overtime for workers until the highest crowding reached 22 tools at once. This overall demonstrated that the high amount of backlog witnessed within roughly 40% of the model time dragged the mean of tool crowding to reach 5.33 tools in the workshop at all times.

All in all, a high concentration of tools in the workshop, accompanied by the relatively low worker utilization for the baseline case, demonstrates an increased pressure on getting the tools out and causes additional stress on all parties involved. Over time, these strains can cause workers to develop serious musculoskeletal disorders, such as repetitive strain injuries or back problems, which are associated with high costs for both the employees and the case company in terms of medical expenses and reduction in productivity.



(a) Crowding time plot



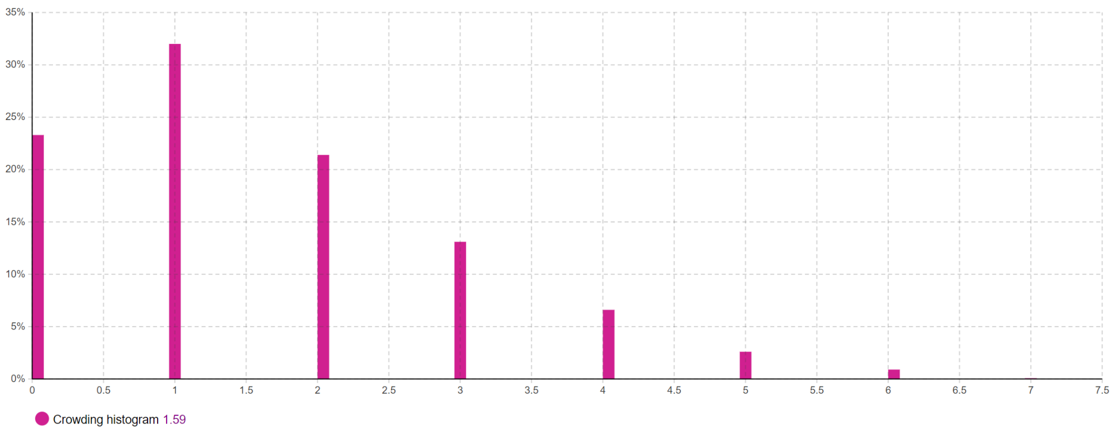
(b) Crowding histogram

Figure 6.6: *Baseline model overview of tool crowding during model run time*

As for the enhanced model, an initial overview of the enhancement was introduced over a time plot in Figure 6.7a, where there was a huge reduction in the overall crowding numbers of tools maintained simultaneously as the majority of peaks were visualized at three tools or lower. Nevertheless, in extreme cases, it peaked at seven tools. This clearly demonstrated the positive impact of the repair-path cycle as the peak was now reduced to less than a third of the baseline, and the graph surge witnessed previously was eliminated.

Moreover, a histogram was added to analyze the differences in peaks of tools over the model run as shown in Figure 6.7b below. The enhanced model showed around 23% of time with zero crowding of tools for maintenance while having the highest peak of approximately 32% with one tool to maintain at a time. Ultimately, around 95% of the three-year period of model run-time witnessed five tools or less crowded within the workshop. This showed a significant amount of backlog reduction. Very low peak points could be seen with six tools simultaneously maintained and a one-off negligible peak for seven tools. The crowding of tool spikes majorly concentrated between the ranges zero and two resulting in a diminished mean of 1.59 tools after the implementation of the repair-path cycle.

(a) Crowding time plot



(b) Crowding histogram

Figure 6.7: *Enhanced model overview of tool crowding during model run time*

Finally, after implementing the repair-path cycle within the enhanced model there was a relatively overall reduction of tool crowding in the workshop, thus, leading to improvements in both the physical ergonomics and the stress levels among the workshop employees. Reduced crowding would allow for easier navigation and less physically strenuous tasks, where it develops a safer, and more reliable work environment. Similarly, with less crowding, workers would experience lower cognitive load and stress levels, contributing to increased job satisfaction and performance.

6.5 Financial Aspects Evaluation

In applying both the baseline and the improved models, three key financial aspects were considered. These included the repair costs for malfunctioning components, the expenses incurred for acquiring new build parts, and the revenues derived from tool rentals for offshore operations. While this financial evaluation is not exhaustive, it offers substantial insight into the primary structural distinctions between the two maintenance procedures and inventory management approaches, hence, labor and administrative costs were not factored in.

Further, it was affirmed through interviews with the tool specialist at the company upon enquiry that there are no holding costs for necessary tools and components due to the presence of an onsite warehouse. This mitigates the need for additional financial allocation for storage.

The financial assessment of the two models yielded critical comparative insights. The enhanced model demonstrated more impressive profit margins than its baseline counterpart. A financial timeline illustrating the revenues, repair costs, and procurement expenses indicated a significant surge in profit margins, estimated at about 3 million. This boost is primarily due to the operational efficiencies of the improved model and the consequential reduction in lead times.

A cooperative combination of decreased repair expenses and increased revenue generation played a considerable role in the financial enhancements observed in the revised model. This proves the viability of the enhanced model in elevating the company's financial performance.

In an effort of visualizing the differences between both model runs, the baseline model financial analysis was introduced over a time plot in Figure 6.8 below presenting the accumulated revenues and costs across the next three years. The graph showed a fairly linear line of revenue, demonstrating how despite the previously seen backlogs of maintenance, the workshop was able to maintain consistent tool output to meet demands over an increased maintenance lead time period. Overall, the revenue had reached 18,630,000 NOK by the end of the model run, while the repair costs reached 1,950,000 NOK, and the Procurement costs 1,537,200 NOK. This left the baseline case a profit of 15,142,800 NOK.

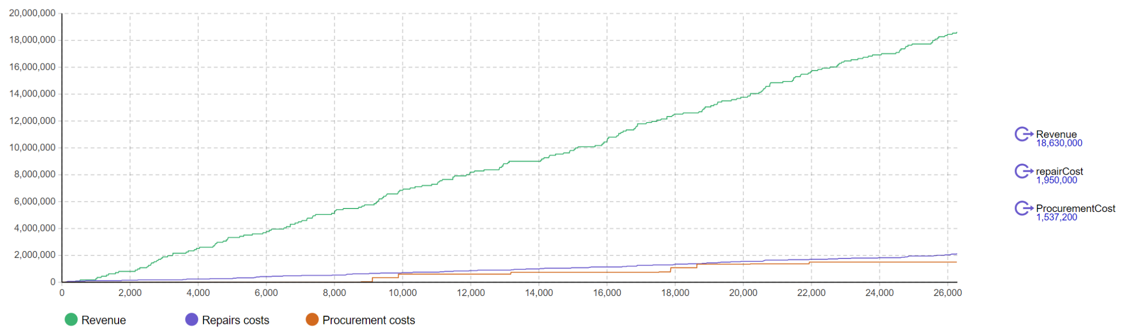


Figure 6.8: *Baseline model financial overview of tools during model run time*

As for the enhanced model, there were some differences when it came to the final values outputted at the end. However, similar trends on the time plot shown in Figure 6.9 could be observed showing that both models were able to continuously output tools at the end of the day, despite their differences in delay times. The final values revealed an increase in gross revenue, shown by the 21,870,000 NOK gross revenue. However, repair costs were slightly higher than the baseline reaching 2,100,000 NOK due to the higher dependence on repairs, with the procurement costs not being significantly different and sitting at 1,564,400 NOK by the end of the third year. This left the case company with an increased net profit reaching 18,205,600 NOK.

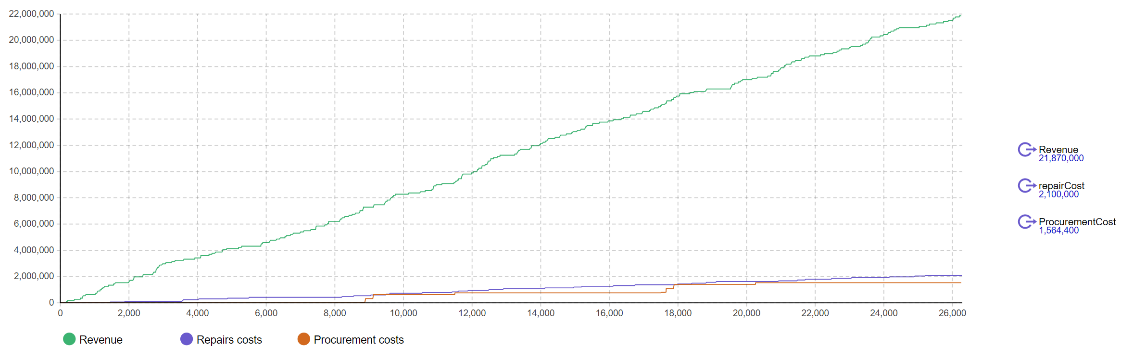


Figure 6.9: *Enhanced model financial overview of tools during model run time*

Despite higher repair costs, the enhanced model leverages efficiencies to increase gross revenue and ultimately, net profit. The increase in revenue and profit indicates that the improved model has successfully mitigated the inefficiencies inherent in the baseline model, leading to more productive use of resources and lower lead times. However, it was expected to see lower procurement costs for the enhanced model, but with the increased circulation of tool maintenance, more tools were maintained leading to a similar procurement cost output by the end of the model run time. This shows the relative advantage of the enhanced model, where if the model were to take similar tool maintenance capacity throughout the model run time, lower costs would have been achieved.

In summary, while both models have their merits, the enhanced model appears to offer a more efficient and profitable solution for the case company. These insights can guide strategic decision-making to optimize the balance between costs, lead times, and revenue generation.

6.6 Model Evaluation and Discussion

In this study, a comparison was conducted between the baseline and enhanced models in terms of their operational efficiency, crowding levels, and financial performance. Both models presented distinct attributes and showed differing strengths and weaknesses, but overall, the enhanced model proved superior in several key areas.

In terms of lead times, the enhanced model showed a significant reduction compared to the baseline model. The average lead time in the enhanced model was only 22% of that in the baseline model, a reduction largely due to the introduction of the repair-path cycle. This cycle facilitated quicker component replacements and repairs, drastically speeding up tool dispatch from the workshop. For the baseline model, the average lead time during the three-year simulation was 888.65 hours, but the enhanced model showed a substantial decrease to 193.09 hours, even accounting for outlier cases.

Worker utilization also improved significantly in the enhanced model. The average utilization surged from 0.73 in the baseline model to 1.58 in the enhanced model, suggesting that the repair-path cycle led to a more efficient use of the workforce. It reduced idle time for workers and enabled a smoother flow of maintenance activities. While the baseline model saw workers idle for about half of the time, idle time was reduced to less than 25% in the enhanced model, with a higher frequency of simultaneous worker utilization.

Crowding levels in the workshop were another area of improvement. The baseline model showed escalating tool accumulation over time, peaking at 22 tools in the third year, raising ergonomic and stress concerns among the workers. In comparison, the enhanced model reduced the crowding levels significantly, with a peak of only seven tools. This reduction in crowding resulted in a safer, more efficient work environment and reduced the average number of tools in the workshop at any given time.

On the financial front, the enhanced model outperformed the baseline model despite higher repair costs. The operational costs in the baseline model ate into the profit margins, resulting in a net profit of 15,142,800 NOK. In contrast, the enhanced model, while having marginally higher repair costs, saw a considerable increase in revenue, yielding a net profit of 18,205,600 NOK. The operational efficiencies and shorter lead times in the enhanced model led to more effective resource utilization, outweighing the increased repair costs.

Collectively, these results suggest that the introduction of the repair-path cycle in the spare parts inventory management system results in considerable improvements as it offers a more sustainable and profitable solution. It successfully mitigates the crowding issues inherent in the baseline model, enhancing operational efficiency, worker well being, and ultimately, financial performance. These findings substantiate the effectiveness of the proposed approach, aligning with works of other researchers. Table 6.1 is presented below demonstrating all obtained results for comparison purposes.

Table 6.1: *Summary of result metrics.*

Metric/Model	Baseline Model	Enhanced Model
Average Lead Time (hours)	888.65	193.09
Lead Time Reduction (%)	-	78%
Worker Utilization (Mean)	0.73	1.58
Increase in Worker Utilization (%)	-	116%
Tools with Lead Time (0 - 500 hours) (%)	≈ 20%	≈ 90%
Tools with Lead Time (>500 hours) (%)	≈ 75%	≈ 5%
Worker Idle Time (%)	≈ 50%	≈ 25%
Workshop Crowding Reduction (%)	-	≈ 73%
Increase in overall Revenue (NOK)	-	3,062,800
Scrap rate (components)	21	10

The insights drawn from this comparison can guide decision-makers strategically in optimizing workshop operations, leading to improved balance between costs, lead times, and revenue generation. It's worth noting that real-life implementation may present unforeseen challenges that were not apparent in the model. Therefore, ongoing monitoring and adjustment will be necessary as part of the implementation process.

It's critical to remember that the findings presented are based on the specific case study and the data accumulated for this research. Further validation of the improved model's performance can be pursued via real-world implementation and comparison with actual operational data.

All simulated indicators can potentially be measured in the real-world application. Such as the tool maintenance velocities, lead times, and worker utilization within the maintenance workshop, however, even after implementation, there will be noticed differences from the obtained results due to the lack of coverage of all components present on tool and the accuracy of logging times from workshop employees.

Chapter 7

Conclusion

The chapter aims to provide a holistic overview of what was achieved throughout the research and open the door for further future improvements.

In summary, the research question revolving around what effects the implementation of a repaired-path cycle process within the maintenance process can do to the lead time of tool maintenance was answered within the enhanced model showing its outperformance of the baseline model in several key metrics. This included operational efficiency with 78% reduction in lead times, worker utilization improvement by 116%, crowding levels reduction by 73%, scrap rate reduction by 52%, and a financial performance increase by roughly three million NOK (20%) in profit generation. Overall, the findings from this thesis suggest that the enhanced model offers a more sustainable, efficient, and profitable solution. These insights can guide strategic decisions in optimizing workshop operations with such geographical constraints, where the sensitivity of these results highly depended on the high procurement lead times.

Regarding the second research question of how this repair-path cycle can be practically modeled is answered through the utilization of a visual simulation approach rather than an analytical one, due to the higher transparency and understanding of complexities. Moreover, structural practicalities such as the extracting and implementing probabilities from the real-world historical data in order to feed the splitting pathways of maintenance. This also extends to the shifting of stocks to cover up the needs of the maintained tools by shifting components between new build stocks and repaired stocks through a state chart in the enhanced Anylogic model.

Though there is a well-known simulation modeling approach structure applied in the scientific world, these two aspects made the model more practical for the case presented and provided solutions for issues that were unforeseen previously during the construction of the baseline model.

This thesis aimed to enhance the inventory management system of a case company, driven by the challenges of long lead times in the offshore operations context. Utilizing both AnyLogic and Python, models of the existing system and an enhanced system were developed to conduct comparative analyses. The need for shorter lead times in such a short cycle region underpinned this research, with the ultimate goal of increasing tool utilization frequency and profit margins.

The enhanced model, in particular, incorporated a repair-path cycle and a splitting approach that detached tools from failed parts. This allowed the repair of failed components independently, while the tool was fitted with a replacement part from the repair stock and promptly dispatched. Coupled with the min-max stock values and re-order points system, these strategic modifications resulted in reduced lead times and more efficient inventory management.

The implementation of the repair-path cycle introduced batch processing of tools for repairs, leading to cost efficiencies. This batch repair approach further underpinned a future-proofing strategy. In this strategy, multiple areas of the tool were repaired at once, irrespective of the current failure, aiming to reduce the frequency of heat treatments and, therefore, the tool's yield strength reductions. Such a comprehensive repair strategy, if executed correctly, could substantially decrease scrap rates and ensure the future reliability of the tools.

Nevertheless, it's important to acknowledge that real-life implementation may present challenges that weren't apparent in the models. Geographic constraints, varying long procurement lead times, and the inclusion of all the different components within the tool posing challenges when implementing the enhanced model. Therefore, continuous monitoring, adjustments, and future research should be a crucial part of the implementation process. This can be assisted by the scaling up of the model to include higher levels of data points in order to reflect each and every component within the discussed tool. The model implemented included the top five components, however, there are forty other core components which in turn will reduce the realistic reflection on real-life implementation. Once achieved, the model can further scale up by including the whole fleet of tools as different agents within the model being maintained at the workshop in hand. This requires drastically higher time allocation, and data budgeting for software development.

Further research can build upon the work conducted in this thesis, with various paths promising potential improvements. One such area could be the development and evaluation of alternative future-proofing strategies or enhancements to the repair-path cycle stock inputs. This exploration could yield significant benefits in terms of operational efficiency and tool life-cycle management. This optimization can be achieved through finding the optimal stock value inputs. It can be represented by the minimum inventory stock values that reflect an elimination of holdings happening throughout the model run time. And therefore, showing no delays at all caused by the repairs and/or replacements. Once this optimization is obtained, the variation of inventory stock policies becomes achievable as to suit the needs and requirements tailored for the case company at hand. Alongside this, investigating more sophisticated stock management techniques, such as dynamic stock optimization based on real-time data, could lead to noteworthy advancements in the model's performance. Such advancements in stock management can be particularly effective when paired with advanced optimization algorithms.

The integration of more advanced optimization algorithms could also serve to significantly boost the effectiveness of the inventory management system. Notably, techniques such as Particle Swarm Optimization, and Simulated Annealing having demonstrated their utility in addressing inventory management challenges. An article by Xu et al., for instance, successfully applied a dynamic programming-based particle swarm optimization algorithm to inventory management under uncertain conditions. The incorporation of such sophisticated optimization algorithms into the existing model offers a compelling direction for future research, potentially revolutionizing the system's efficiency and profitability [41].

In light of the growing emphasis on sustainable business practices, future research could focus on how the enhanced model could help such companies advance their environmental performance. Potential modifications might include strategies to minimize material waste, diminish energy consumption, and consider the life-cycle impacts of distinct inventory management approaches. As explained by Srivastava, the intersection of inventory management and environmental consciousness, often referred to as Green Inventory Management, represents a significant opportunity for operational improvement while fulfilling sustainability goals [42].

Ultimately, this study serves as a stepping stone towards achieving a more effective, efficient, and sustainable workshop operation, paving the way for future research and improvements.

Bibliography

[1] O. Bounou, A. El Barkany, and A. El Biyaali, "Performance indicators for spare parts and maintenance management: an analytical study," *Journal of Engineering*, vol. 2020, pp. 1–22, 2020.

[2] Y. L. Koçağa and A. Şen, "Spare parts inventory management with demand lead times and rationing," *IIE Transactions*, vol. 39, no. 9, pp. 879–898, 2007.

[3] X. Li, K. Zhang, and Z. Tan, "Spare part management in a testing workshop," in *2015 Winter Simulation Conference (WSC)*, pp. 3170–3171, IEEE, 2015.

[4] P. L. Miranda, R. Morabito, and D. Ferreira, "Mixed integer formulations for a coupled lot-scheduling and vehicle routing problem in furniture settings," *INFOR: Information Systems and Operational Research*, vol. 57, no. 4, pp. 563–596, 2019.

[5] U. Ali, B. Salah, K. Naeem, A. S. Khan, R. Khan, C. I. Pruncu, M. Abas, and S. Khan, "Improved mro inventory management system in oil and gas company: Increased service level and reduced average inventory investment," *Sustainability*, vol. 12, no. 19, p. 8027, 2020.

[6] M. F. Saeed Osman, "Modeling and simulation for inventory management of repairable items in maintenance systems," *Simulation*, vol. 98, no. 11, pp. 1013–1037, 2022.

[7] S. Van der Auweraer and R. Boute, "Forecasting spare part demand using service maintenance information," *International Journal of Production Economics*, vol. 213, pp. 138–149, 2019.

[8] H. H. Turan, M. Atmis, F. Kosanoglu, S. Elsawah, and M. J. Ryan, "A risk-averse simulation-based approach for a joint optimization of workforce capacity, spare part stocks and scheduling priorities in maintenance planning," *Reliability Engineering & System Safety*, vol. 204, p. 107199, 2020.

[9] S. Nahmias and T. L. Olsen, *Production and operations analysis*. Waveland Press, 2015.

[10] L. J. Krajewski, L. P. Ritzman, and M. K. Malhotra, *Operations management.* Pearson Education UK, 2013.

[11] R. Ramanathan, “Abc inventory classification with multiple-criteria using weighted linear optimization,” *Computers & operations research*, vol. 33, no. 3, pp. 695–700, 2006.

[12] S. Axsäter, *Inventory control*, vol. 225. Springer, 2015.

[13] W. Kennedy, J. W. Patterson, and L. D. Fredendall, “An overview of recent literature on spare parts inventories,” *International Journal of production economics*, vol. 76, no. 2, pp. 201–215, 2002.

[14] M. H. Al-Rifai and M. D. Rossetti, “An efficient heuristic optimization algorithm for a two-echelon (r, q) inventory system,” *International Journal of Production Economics*, vol. 109, no. 1-2, pp. 195–213, 2007.

[15] G. Tagaras and D. Vlachos, “A periodic review inventory system with emergency replenishments,” *Management Science*, vol. 47, no. 3, pp. 415–429, 2001.

[16] S. Zhu, W. van Jaarsveld, and R. Dekker, “Spare parts inventory control based on maintenance planning,” *Reliability Engineering & System Safety*, vol. 193, p. 106600, 2020.

[17] G. E. Box, G. M. Jenkins, G. C. Reinsel, and G. M. Ljung, *Time series analysis: forecasting and control.* John Wiley & Sons, 2015.

[18] R. J. Hyndman and G. Athanasopoulos, *Forecasting: principles and practice.* OTexts, 2018.

[19] T. R. Willemain, C. N. Smart, and H. F. Schwarz, “A new approach to forecasting intermittent demand for service parts inventories,” *International Journal of forecasting*, vol. 20, no. 3, pp. 375–387, 2004.

[20] F. Johnston and J. E. Boylan, “Forecasting for items with intermittent demand,” *Journal of the operational research society*, vol. 47, no. 1, pp. 113–121, 1996.

[21] R. H. Teunter, A. A. Syntetos, and M. Z. Babai, “Intermittent demand: Linking forecasting to inventory obsolescence,” *European Journal of Operational Research*, vol. 214, no. 3, pp. 606–615, 2011.

[22] J. VanderPlas, *Python data science handbook: Essential tools for working with data.* " O’Reilly Media, Inc.", 2016.

[23] W. McKinney *et al.*, “Data structures for statistical computing in python,” in *Proceedings of the 9th Python in Science Conference*, vol. 445, pp. 51–56, Austin, TX, 2010.

[24] M. Abadi, P. Barham, J. Chen, Z. Chen, A. Davis, J. Dean, M. Devin, S. Ghemawat, G. Irving, M. Isard, *et al.*, "Tensorflow: a system for large-scale machine learning.," in *Osdi*, vol. 16, pp. 265–283, Savannah, GA, USA, 2016.

[25] N. ISO, "14224: 2016 petroleum, petrochemical and natural gas industries-collection and exchange of reliability and maintenance data for equipment," *ISO*, vol. 14224, pp. 2016–09, 2016.

[26] A. W. Labib, "A decision analysis model for maintenance policy selection using a cmms," *Journal of Quality in Maintenance Engineering*, vol. 10, no. 3, pp. 191–202, 2004.

[27] N. petroleum industry, "Risk-based maintenance and consequence classification." `https://www-standard-no.ezproxy.uis.no/en/PDF/FileDownload/?redir=true&filetype=Pdf&preview=true&item=956000&category=5`, 2017.

[28] F. I. Khan and M. M. Haddara, "Risk-based maintenance (rbm): a quantitative approach for maintenance/inspection scheduling and planning," *Journal of loss prevention in the process industries*, vol. 16, no. 6, pp. 561–573, 2003.

[29] E. A. Silver, D. F. Pyke, R. Peterson, *et al.*, *Inventory management and production planning and scheduling*, vol. 3. Wiley New York, 1998.

[30] J. Rego and M. Mesquita, "Spare parts inventory control: A literature review," *Produção*, vol. 21, pp. 656–666, 01 2011.

[31] AnyLogic-Company, "Anylogic simulation software." `https://www.anylogic.com/`, 2023.

[32] T. Wu, J. Blackhurst, and P. O'grady, "Methodology for supply chain disruption analysis," *International journal of production research*, vol. 45, no. 7, pp. 1665–1682, 2007.

[33] A. Negahban and J. S. Smith, "Simulation for manufacturing system design and operation: Literature review and analysis," *Journal of manufacturing systems*, vol. 33, no. 2, pp. 241–261, 2014.

[34] A. Borshchev, "Multi-method modelling: Anylogic," *Discrete-Event Simulation and System Dynamics for Management Decision Making*, pp. 248–279, 2014.

[35] S. U. Seçkiner and A. Koç, "Agent-based simulation and simulation optimization approaches to energy planning under different scenarios: A hospital application case," *Computers & Industrial Engineering*, vol. 169, p. 108163, 2022.

[36] R. K. Yin, *Case study research: Design and methods*, vol. 5. sage, 2009.

[37] J. W. Creswell, "Research designs: Qualitative, quantitative, and mixed methods approaches," *Callifornia: Sage*, 2009.

[38] C. Teddlie and A. Tashakkori, "Mixed methods research," *The Sage handbook of qualitative research*, vol. 4, pp. 285–300, 2011.

[39] N. K. Denzin and Y. S. Lincoln, *The Sage handbook of qualitative research.* sage, 2011.

[40] T. Aven, *Risk analysis.* John Wiley & Sons, 2015.

[41] J. Xu, Z. Zeng, B. Han, and X. Lei, "A dynamic programming-based particle swarm optimization algorithm for an inventory management problem under uncertainty," *Engineering Optimization*, vol. 45, no. 7, pp. 851–880, 2013.

[42] S. K. Srivastava, "Green supply-chain management: a state-of-the-art literature review," *International journal of management reviews*, vol. 9, no. 1, pp. 53–80, 2007.