Solid Waste Processing Facility Improvement Using Lean Principles and Simulation Modeling

by

Mohamad Ramadan

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Department of Civil and Environmental Engineering
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Abstract

Municipal solid waste (MSW) management presents a significant challenge, as current practices often lead to inefficiencies and substantial variability in waste processing. This variability contributes to increased downtime, reduced productivity, and higher operational costs. While previous research has targeted specific areas of waste management optimization, there remains a need for a comprehensive approach that addresses these challenges holistically across the entire waste processing system.

This thesis introduces a framework aimed at analyzing and optimizing the operations of a municipal solid waste processing facility, grounded in Lean Thinking and Theory. The study utilized historical data from a solid waste management facility (SWMF), specifically its refuse-derived fuel (RDF) process, to test and validate the proposed framework.

Using Lean tools such as Value Stream Mapping and Simulation Modelling, the study evaluated the current state of operations at the SWMF. These tools helped identify inefficiencies, and a base-case scenario was developed to serve as a benchmark for testing potential improvements. Key metrics such as downtime percentage, total runtime, and total throughput were analyzed. The study proposed three main interventions: implementing preventive maintenance, reducing repair times through better inventory management, and optimizing the use of the facility's dual processing lines to mitigate the impact of equipment breakdowns.

In conclusion, the study provided a detailed analysis of the waste processing system at both micro and macro levels. Simulation modelling demonstrated that combining the proposed interventions could significantly reduce downtime, increase throughput, and improve overall operational efficiency. This case study offers a foundation for future research and the adoption of Lean practices in waste management facilities, with the potential to enhance sustainability and operational performance.

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Preface

This thesis is an original work by Mohamad Ramadan. No part of this thesis has been previously published.

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Chapter 1 – Introduction

1.1. Background and Problem Statement

From 2002 to 2018, the amount of solid waste generated in Canada surged by 4.8 million tons, reaching 35.6 million tons. Concurrently, the volume of waste disposed of via landfills or incineration rose by 1.7 million tons, culminating to 25.7 million tons. In 2018, only 28% of solid waste was diverted from disposal, with the remaining 72% sent to landfills or incinerators (Canada.ca, 2022). Efficient and sustainable management of Municipal Solid Waste (MSW) remains a significant challenge for municipal governments (Badran et al., 2006). The growing volume and variety of MSW in large urban areas underscore the urgent need for developing comprehensive operational and strategic plans to achieve long-term sustainability goals and minimize the risk of service disruptions (Tan et al., 2014).

Current research perceives waste management as an Integrated Solid Waste Management (ISWM) problem and proposes myriad optimization solutions. These include optimizing efficient vehicle routing through new frameworks (Mojtahedi et al., 2021), maximizing the cost-effective ISWM system by examining an integrated framework of the fleet size and Mix Vehicle Routing Problem (VRP), and improving the supply chain network of waste management (Asefi et al., 2019).

Literature also points out the aspect of converting municipal solid waste into refuse-derived fuel, focusing on compliance with quality standards (Gallardo et al., 2014) and environmental impacts (Grzesik et al., 2016). Tahir et al. (2023), investigates the production of refuse-derived fuel using network flow modeling, addressing quality uncertainties to optimize fuel output from municipal solid waste. Other research utilized simulation modeling to solve the problem from the perspective of economy, energy recovery (Sadati et al., 2023), as well as waste facility location, incorporating system resilience alongside cost, pollution, and social factors (Duan et al, 2024).

Production systems in waste management also pose challenges as they often result in high variability in the production flow, prohibiting the sustainable implementation of lean practices (Richter et al., 2022). As the decision-aid tools available in the industry are generally unreliable to address these problems, some solutions proposed by researchers include developing simulation models of the entire waste management process (Villeneuve et al., 2003).

Chen et al. (2023) stresses the significance of studying variability in municipal solid waste (MSW) streams for effective waste management. The authors discuss how variability in MSW streams can affect the waste process efficiency and suggest that understanding these variabilities can improve the design of the waste management system. Characterizing and managing this variability is crucial for optimizing process efficiency, product quality, and environmental sustainability. They provide examples of strategies for managing variability, such as adjusting the process parameters and utilizing different processing techniques. (Liu et al., 2009).

Furthermore, a report by the United Nations Environment Programme (UNEP) states that reducing variability in waste composition is critical for improving the efficiency and effectiveness of waste processing and management systems. The report highlights the importance of understanding the sources and nature of variability in waste streams (UNEP, 2024). Similarly, a report by the European Union's (EU) Joint Research Centre emphasizes how the variability in waste processes can impact the quality of the final product and increase the risk of environmental pollution (European Union Joint Research Centre, 2023).

Al-Tahat et al. (2013) explore the relationship between lean production and variability reduction. They conduct a systematic literature review to examine how lean practices, such as value stream mapping, contribute to reducing process variability. Moreover, they discuss the impact of implementing lean principles on improving process stability and reducing variability in manufacturing processes. In lean production, the general path of success is emphasized by maximizing capability and availability while reducing variability (Womack et al., 1997).

Based on a review of construction literature and extensive discussions with stakeholders in the construction industry, a research gap has been identified: There is a need for more research that considers the processing aspect of waste facilities to address the problem of variability in the system. More specifically there’s a gap in the literature on the effects of Lean production on the Refuse-divided fuel production in a solid waste management facility, in the aspects of repair times and breakdown probability.

This research aims to assess and suggest interventions to the waste management process of the solid waste management facility by identifying and removing variabilities and wastes in the process. This will be achieved by developing a simulation model for SWMF inspired by lean theory in production and applying lean tools and techniques.

1.2 Research Objectives

- Replicate the real-world solid waste processing facility through a simulation model that can be used to investigate different scenarios, and
- Develop and validate a set of lean interventions that are aimed to reduce downtime, and repair time to increase the production output.

1.3 Contribution

1.3.1 Academic Contribution

- Providing a methodology for developing a simulation model framework designed for a waste processing facility; and,
- Providing analyses of tested scenarios for improvement of waste facilities.

1.3.2 Industry Contribution

- Developing a framework for a simulation model that can be adopted in waste processing facilities, serving as a decision-aid tool; and
- Developing a roadmap to assess outcomes of tested scenarios for improvement of waste facilities.

1.4 Research Methodology

The research methodology adopted for this thesis is Design Science Research (DSR). The first step in this study was to observe the facility in running conditions and collect data, to develop a value stream map, which is validated with an expert panel. Then collecting historical data from the facility database. Leading to the development of a simulation model of the real-life facility, where domain experts and historical data allow the validation of the model. Opening the door to analysing possible interventions and modeling them, and finally analyze the applied method's outcomes and provide recommendations to improvements. The research methodology is explained in chapter three.

1.5 Organization of thesis

This thesis is structured into eight chapters, each contributing to the comprehensive exploration of improving municipal solid waste management at the Solid Waste Management Facility (SWMF). Chapter 1 introduces the background, problem statement, and research objectives that guide the study. Chapter 2 provides a detailed literature review, focusing on lean thinkinh principles, value stream mapping, and simulation modeling, which form the theoretical foundation for the research. Chapter 3 outlines the research methodology, specifically Design Science Research, and explains the steps taken to develop the simulation model used to assess the current state of the SWMF. Chapter 4 offers a detailed description of the SWMF's waste processing system, from the initial tipping floor to the final processing stages and identifies potential areas for improvement. Chapter 5 presents the development and validation of the Value Stream Map, which visually represents the current state of the SWMF 's processes. Chapter 6 details the creation, verification, and validation of the simulation model, which replicates the real-world operations of the SWMF and provides key metrics for analysis. Chapter 7 explores various lean interventions aimed at reducing downtime and improving throughput at the facility, including the simulation of these interventions and the analysis of their potential impact. Finally, Chapter 8 concludes the study by summarizing the findings, discussing the limitations of the research, and offering recommendations for future studies in the field of waste management.

Chapter 2 – Literature Review

2.1 Introduction

Solid waste processing facilities are crucial in managing the ever-increasing amounts of waste generated by urban populations and industrial activities. Despite significant advancements in technology and operations, these facilities face challenges related to efficiency, cost-effectiveness, and environmental impact. The effective management of solid waste is essential not only for maintaining environmental health but also for optimizing resource utilization and operational costs (Yuehong et al., 2006). The integration of Lean Thinking into the manufacturing sector has demonstrated considerable success in addressing similar challenges. Lean principles, particularly Value Stream Mapping (VSM) and Simulation Modeling have proven to be powerful tools for identifying inefficiencies, reducing waste, and improving overall process performance (Womack & Jones, 1997). The study presented in this thesis focuses on the production system in a solid waste processing facility. The following sections will delve deeper into the benefits of these approaches in manufacturing.

2.2 Lean Manufacturing

2.2.1. Lean Thinking

Lean thinking is a systematic approach aimed at minimizing waste within a manufacturing system while simultaneously maximizing productivity. Originating from the Toyota Production System (TPS) in Japan during the late 1940s, lean manufacturing emphasizes efficiency, continuous improvement, and value creation from the customer's perspective (Ohno, 1988). Central to lean philosophy is the concept of "Kaizen," which translates to "continuous improvement," encouraging all employees, from top management to shop floor workers, to identify and eliminate waste in every aspect of production processes (Imai, 1986). This waste, termed "Muda" in Japanese, includes any activity that consumes resources without adding value, such as overproduction, waiting times, excess inventory, and unnecessary motion (Womack & Jones, 1997).
Lean thinking also incorporates principles like "Just-In-Time" (JIT) production, which focuses on producing what is needed, when it is needed, thereby reducing inventory costs and improving cash

flow (Monden, 1993). Another core principle is "Jidoka," or automation with a human touch, which ensures that machines stop automatically when defects are detected, allowing immediate problem resolution (Liker, 2004). Standardized work processes and visual management tools, such as Kanban systems, are used to streamline operations and enhance communication and coordination among team members (Rother & Shook, 1999).

Five fundamental principles of Lean were identified by Womack and Jones (2003), which included (1) Defining value from the customer's perspective, (2) Mapping the entire value stream for each product and eliminating waste, (3) Ensuring the flow of value-creating steps, (4) Producing only what the customer wants, when they want it, (5) Striving for perfection by continually reducing effort, time, space, cost, and errors.

Moreover, lean manufacturing fosters a culture of respect for people, recognizing that empowered and engaged employees are critical to the success of lean initiatives (Liker & Hoseus, 2008). By involving workers in decision-making and problem-solving processes, organizations can tap into their insights and foster a sense of ownership and accountability (Spear & Bowen, 1999). The lean approach also emphasizes the importance of supplier integration and collaboration to ensure the entire supply chain operates efficiently and responsively (Womack et al., 1990).

Adopting lean thinking can lead to significant improvements in product quality, production speed, and overall operational efficiency. It not only helps reduce costs and increase profitability but also enhances customer satisfaction by delivering higher-quality products promptly (Womack et al., 2003). As industries worldwide continue to face competitive pressures and the need for sustainable practices, lean manufacturing remains a pivotal strategy for achieving long-term success and adaptability in a dynamic market landscape (Hines et al., 2004).

Technology is vital in Lean implementation, utilizing tools such as Value Stream Mapping, Virtual Models, the Last Planner System, and Target Value Design (Hamzeh, 2021). Additionally, Lean production ensures material quality and quantity, minimizing waste while maintaining the flexibility to adapt to production variability (Bajjou & Chafi, 2020; Mao & Zhang, 2008).

2.2.2. Manufacturing Waste Concept and Lean

Manufacturing waste and downtime are critical issues that impact manufacturing operations' efficiency, productivity, and profitability. Waste in manufacturing refers to any activity that consumes resources without adding value to the final product, while downtime refers to periods when production is halted. Both waste and downtime can lead to significant financial losses, reduced competitiveness, and decreased customer satisfaction.

The concept of waste in manufacturing, also known as "Muda" in Japanese, originates from the Toyota Production System (TPS). Taiichi Ohno, the architect of TPS, identified seven types of waste that hinder manufacturing processes: overproduction, waiting, transporting, inappropriate processing, unnecessary inventory, unnecessary motion, and defects (Ohno, 1988). Overproduction occurs when more products are produced than needed, leading to excess inventory and increased storage costs. Waiting involves idle time when resources are not in use, often due to bottlenecks or unbalanced workloads. Transporting refers to the unnecessary movement of materials or products, which does not add value and increases the risk of damage.

Inappropriate processing involves using more complex or expensive processes than necessary, while unnecessary inventory ties up capital and space, increasing storage costs and risk of obsolescence. Unnecessary motion includes any movement by workers that does not add value, such as searching for tools or materials. Lastly, defects result in rework or scrap, directly affecting product quality and customer satisfaction (Womack & Jones, 1997).

Downtime is another significant issue in manufacturing, defined as any period during which production is stopped. Downtime can be planned, such as during maintenance, or unplanned, such as due to equipment failures, lack of materials, or labor shortages. Unplanned downtime is particularly costly, as it disrupts production schedules, leads to missed deadlines, and reduces overall equipment effectiveness (OEE) (Smith, 2011). The financial impact of downtime can be substantial, with some industries reporting losses of thousands of dollars per minute of downtime (Mobley, 2002).

Manufacturing waste and downtime are critical issues that can severely impact the efficiency and profitability of manufacturing operations. Lean thinking offers a comprehensive approach to addressing these challenges by focusing on waste reduction, continuous improvement, and value creation. The principles of lean thinking, such as JIT production, Jidoka, and Kaizen, have proven effective in enhancing operational efficiency and customer satisfaction. As industries continue to face competitive pressures and the need for sustainable practices, lean thinking remains a pivotal strategy for achieving long-term success and adaptability in a dynamic market landscape (Hines et al., 2004).

2.3. Value Stream Mapping

Value Stream Mapping (VSM) is a lean-management method used for analyzing and designing the flow of materials and information required to bring a product or service to a consumer. Originating from the Toyota Production System, VSM helps organizations visualize the steps involved in their processes, identify waste, and improve overall efficiency (Rother & Shook, 1999). By focusing on the entire value stream, rather than individual processes, VSM enables organizations to see the big picture and make more informed decisions about where to focus their improvement efforts.

The importance of VSM lies in its ability to provide a comprehensive view of an organization's processes, highlighting areas where value is added and where waste occurs. This holistic perspective is crucial for identifying inefficiencies, redundancies, and bottlenecks that may not be apparent when examining processes in isolation (Hines & Rich, 1997). VSM helps organizations streamline their operations, reduce lead times, and improve product quality, ultimately leading to increased customer satisfaction and competitive advantage.

One of the key benefits of VSM is its ability to facilitate communication and collaboration across different departments and functions within an organization. By creating a visual representation of the value stream, VSM helps break down silos and encourages a more integrated approach to process improvement (Rother & Shook, 1999). Additionally, VSM provides a common language and framework for discussing and addressing process inefficiencies, making it easier for teams to align their efforts and work towards shared goals.

Several tools and techniques are commonly used in VSM to capture and analyze the flow of materials and information. Some of the most important tools include:

1. Current State Map: This tool captures the existing processes and workflows within the value stream, highlighting areas where waste occurs and where improvements are needed.

The current state map provides a baseline for measuring progress and identifying opportunities for improvement.

2. Future State Map: This tool outlines the desired future state of the value stream, incorporating proposed changes and improvements. The future state map serves as a blueprint for implementing lean initiatives and achieving the organization's process improvement goals.
3. Process Flow Diagrams: These diagrams provide a detailed view of individual processes within the value stream, showing the sequence of steps and the flow of materials and information. Process flow diagrams help identify specific areas where waste occurs and where improvements can be made.
4. Takt Time Analysis: Takt time is the rate at which a product must be produced to meet customer demand. Takt time analysis helps organizations align their production processes with customer requirements, ensuring that resources are used efficiently, and that production meets demand (Rother & Shook, 1999).
5. Value Stream Metrics: Key performance indicators (KPIs) and metrics are used to measure the efficiency and effectiveness of the value stream. Common metrics include lead time, cycle time, inventory levels, and defect rates. These metrics help organizations track their progress and identify areas for further improvement.

VSM is widely used across various industries and sectors, including manufacturing, healthcare, logistics, and services. Its flexibility and adaptability make it a valuable tool for any organization seeking to improve its processes and deliver greater value to customers.

1. Manufacturing: In manufacturing, VSM is used to analyze production processes, identify bottlenecks, and reduce waste. By optimizing the flow of materials and information, manufacturers can improve efficiency, reduce lead times, and enhance product quality (Rother & Shook, 1999).
2. Healthcare: In the healthcare sector, VSM is used to streamline patient care processes, reduce waiting times, and improve the overall patient experience. By mapping the flow of patients, information, and resources, healthcare organizations can identify inefficiencies and implement changes to enhance service delivery (Graban, 2018).

3. Logistics and Supply Chain Management: VSM is used in logistics and supply chain management to optimize the flow of goods and information from suppliers to customers. By analyzing and improving processes such as order fulfillment, transportation, and inventory management, organizations can reduce costs, improve delivery times, and enhance customer satisfaction (Lummus & Vokurka, 1999).
4. Services: In the service industry, VSM is used to analyze and improve processes such as customer service, order processing, and administrative tasks. By identifying and eliminating waste, service organizations can enhance efficiency, reduce costs, and improve the overall customer experience (Swank, 2003).

Value Stream Mapping is a powerful tool for organizations seeking to improve their processes, reduce waste, and deliver greater value to customers. By providing a comprehensive view of the value stream, VSM helps organizations identify inefficiencies, streamline operations, and achieve their process improvement goals. Its applicability across various industries and sectors makes it an essential component of any lean-management strategy. As organizations continue to face competitive pressures and the need for sustainable practices, VSM remains a vital tool for achieving long-term success and operational excellence.

2.4. Manufacturing Simulation Modelling

Manufacturing simulation modeling involves creating a virtual representation of a manufacturing process or system. This allows engineers and managers to analyze and visualize the behavior of the system under various conditions without physically altering the real-world system. Simulation modeling is used to predict performance, identify bottlenecks, optimize processes, and improve decision-making in manufacturing environments (Banks & Carson, 1984). Simulation modeling is crucial in manufacturing for several reasons. It enables the testing of different scenarios and the assessment of potential changes to processes without disrupting actual production. This is particularly important in complex manufacturing systems where trial-and-error methods can be costly and time-consuming (Law & Kelton, 2007).

2.4.1. Key aspects of simulation modeling

1. Modeling the Process: This involves defining the components and interactions within the system, including machines, workers, materials, and information flow (Banks & Carson, 1984).
2. Running Simulations: By running simulations, users can observe the behavior of the system under different conditions and identify areas for improvement (Law & Kelton, 2007).
3. Analyzing Results: Simulation results provide insights into system performance, highlighting bottlenecks, inefficiencies, and potential solutions (Robinson, 2014).

2.4.2. Common Types of Simulation Modeling

Discrete Event Simulation (DES) models the operation of a system as a discrete sequence of events in time, where each event occurs at a specific instant and marks a change of state in the system (Banks, 2005). DES is widely used in manufacturing, logistics, healthcare, and telecommunications to model systems like production lines, supply chains, and patient flow in hospitals. Popular software for DES includes Arena, Simul8, and AnyLogic (Law & Kelton, 2007).

Continuous simulation, on the other hand, models systems using differential equations that represent changes in the state variables continuously over time. This type of simulation is commonly applied in fields such as ecology, economics, and engineering to simulate systems like climate models, economic growth, and fluid dynamics (Law & Kelton, 2007). Tools like MATLAB/Simulink, Stella, and Vensim are often used for continuous simulation.

Agent-based modeling (ABM) involves simulating the interactions of individual agents—such as people, animals, or vehicles—to assess their effects on the system as a whole. ABM is extensively used in social sciences, epidemiology, traffic simulation, and market analysis (AnyLogic, n.d.). Software such as NetLogo, AnyLogic, and Repast is typically employed for ABM.

System Dynamics (SD) uses feedback loops and time delays to understand the behavior of complex systems over time. SD is often applied in business, public policy, and environmental studies to model phenomena like economic growth, resource management, and organizational change. Commonly used SD software includes Vensim, Stella, and Powersim (Ventana et al.).

This study adopted AnyLogic as simulation software platform, it is a sophisticated simulation software platform designed to address complex challenges across various industries, including manufacturing. It stands out due to its unique ability to support multiple simulation methodologies, including discrete event simulation (DES), agent-based modeling (ABM), and system dynamics (SD), all within a single model. This flexibility allows users to create highly detailed and accurate models of manufacturing processes and systems (AnyLogic.com, n.d.).

2.4.3. Evolution of Simulation Modeling

Simulation modeling has evolved significantly over the years. Early simulations were performed manually or with rudimentary computer programs, limited in scope and capability. The advent of computers in the 1950s and 1960s allowed for the first digital simulations, primarily focused on military and aerospace applications. The development of dedicated simulation software in the 1970s and 1980s made creating and running models easier, with DES and SD modeling gaining prominence during this period.

The 1990s and 2000s saw the introduction of ABM, providing a new way to model complex systems with interacting agents. Simulation software became more user-friendly, with graphical interfaces and pre-built modules. From the 2010s to the present, integration with big data, machine learning, and cloud computing has expanded simulation modeling capabilities. Real-time simulations and predictive analytics are now possible, allowing for more dynamic and responsive models (Banks, 2005; Law & Kelton, 2007).

2.4.4. Advantages and Limitations of Simulation Modeling

Simulation Modeling has many advantages and benefits including:

1. Risk Reduction: Simulation allows for the assessment of potential risks and the testing of solutions in a virtual environment, minimizing the risk of implementing changes in the real world (Banks, 2005).
2. Cost Efficiency: By identifying inefficiencies and optimizing processes, simulation modeling can significantly reduce operational costs.

3. Improved Decision Making: Simulation provides detailed insights into the behavior of manufacturing systems, enabling better-informed decisions (Robinson, 2014).
4. Enhanced Performance: Simulation helps identify bottlenecks and optimize resource allocation, leading to improved system performance and productivity.
5. Flexibility: Simulation models can be easily adjusted to test various scenarios, providing flexibility in planning and decision-making.
6. Visualization: Graphical representations of simulation models help stakeholders understand complex processes and their interdependencies (Pidd, 1998).

Simulation Modeling faces limitation as well, including:

1. Data Dependency: Simulation models rely heavily on accurate input data. Inaccurate or incomplete data can lead to unreliable outcomes and incorrect decisions. (Law et al., 2007).
2. Complexity: As systems become more complex, creating an accurate simulation can be difficult and time-consuming. Complex models may require advanced programming skills and extensive testing (Banks et al., 2005)
3. Assumptions and Simplifications: To make models manageable, simplifications or assumptions are often made, which can limit their accuracy when compared to real-world conditions (Pidd, 1997)
4. Validation Difficulty**:** Validating a simulation to ensure it truly represents real-world systems can be challenging, as it is often subjective and requires significant expertise (Sargent, 2011).

2.4.5. Simulation Modeling and Waste management

Simulation modeling is particularly valuable in the field of waste management, where it can be used to design, analyze, and optimize waste collection, transportation, and processing systems. Key applications include:

1. Optimizing Waste Collection Routes: Simulation models can be used to design efficient waste collection routes, reducing fuel consumption and operational costs (Das & Bhattacharyya, 2015).

2. Evaluating Recycling Processes: Simulation can help assess and improve recycling processes, identifying bottlenecks, and optimizing resource allocation (Meng et al., 2018).
3. Designing Waste Processing Facilities: Simulation models can assist in the design and layout of waste processing facilities, ensuring optimal flow and utilization of resources (Stephens et al., 2013).
4. Analyzing Waste Generation Patterns: Simulation can be used to analyze waste generation patterns and predict future trends, aiding in strategic planning and policy development (Pires et al., 2011).

2.4.6. Stages of Simulation Modeling

The process of simulation modeling typically involves several stages:

1. Problem Definition: Clearly defining the problem to be addressed and the objectives of the simulation study (Banks, 2005).
2. System Modeling: Creating a detailed model of the system, including all relevant components and their interactions (Law & Kelton, 2007).
3. Data Collection: Gathering data on the system's performance, including process times, resource availability, and demand patterns (Robinson, 2014).
4. Model Verification and Validation: Ensuring that the model accurately represents the real-world system and behaves as expected (Pidd, 1998).
5. Running Simulations: Conducting simulations to observe the behavior of the system under different scenarios and conditions (Kelton et al., 2024).
6. Analyzing Results: Interpreting the simulation results to identify bottlenecks, inefficiencies, and opportunities for improvement (Robinson, 2004).
7. Implementing Changes: Using the insights gained from the simulation to implement changes and optimize the real-world system (Banks, 2005).
8. Monitoring and Refinement: Continuously monitoring the system's performance and refining the model as needed to ensure ongoing improvement (Law & Kelton, 2007).

2.4.7. Graphical Modeling

Graphical modeling is a key component of simulation modeling, providing visual representations of the system and its processes. This helps stakeholders understand complex interactions and identify areas for improvement. Common graphical modeling tools include:

1. Flowcharts: These diagrams represent the sequence of steps in a process, helping to identify and analyze workflows (Pidd, 1998).
2. Process Maps: These maps provide a detailed view of the interactions between different components of a system, highlighting dependencies and bottlenecks.
3. 3D Models: Three-dimensional models offer a realistic visualization of the manufacturing environment, aiding in the design and analysis of processes (Kelton et al., 2024).

2.4.8. Conclusion

In conclusion, manufacturing simulation modeling is a powerful tool for analyzing and optimizing manufacturing processes. By creating simulation models of real-world systems, organizations can identify inefficiencies, reduce costs, and improve overall performance. The importance of simulation modeling lies in its ability to provide detailed insights into system behavior, enabling better decision-making and risk management. With applications across various industries, including waste management, simulation modeling remains an essential component of modern manufacturing strategies. By leveraging advanced tools and methodologies, organizations can enhance their competitiveness and achieve long-term success in a dynamic market environment.

2.5. Conclusion of Chapter

This chapter provides an in-depth exploration of the relevant literature concerning the subjects covered in this study. As this research is grounded in lean thinking and utilizes various methodologies like Value Stream Mapping (VSM), and simulation, the chapter delves into these topics. It starts by examining studies that underscore the importance of Lean Production (LP) and its applicability in manufacturing. Furthermore, it delves into research on VSM. Additionally, this chapter touched on the realm of simulation, shedding light on the advantageous role simulation plays in refining production processes.

Chapter 3 - Methodology

3.1. Introduction

This section introduces the research approach and data collection methods and then describes the main objectives of the thesis.

3.2. Design Science Research

Design Science Research (DSR) is the adopted methodology for this research. DSR aims at solving real-world problems by developing solutions based on science (G. da Rocha et al. 2012), and thoroughly understanding the problems or opportunities (Robinson, 2014). Adopted by many researchers in different domains such as operation management, or information systems. Design Science Research is active in technological artifact development (Kuechler & Vaishnavi, 2012), solving people and organization problems that have been identified by creating and evaluating said IT artifact (Venable et al. 2012). According to March and Smith (1995), Design Science Research (DSR) has two main objectives: the creation of artifacts that address real-world problems and the evaluation of the effectiveness of these artifacts in practical applications.

DSR was chosen for this study because DSR is inherently practical and solution oriented. It emphasizes the creation of artifacts that address real-world problems, making it particularly suitable for research aimed at developing practical solutions rather than just theoretical insights (March & Smith, 1995).

There are three main elements that form the DSR methodology: (1) identification of the problem, (2) development of a solution or artifact, and (3) evaluation of the solution.

3.3. Problem Identification

Increasing throughput and decreasing downtime are essential factors in any manufacturing facility, and by extension, solid waste processing facilities. Excess downtime leads to failure in solid waste processing facilities. This failure translates into Reduced Productivity, Increased Costs, Resource Inefficiency, Customer Dissatisfaction, and Disruption to Continuous Improvement. In DSR the first step of research methodology is the problem identification, which serves as the research motivation.

3.4. Solution Development

The solution development comprises four distinct steps: Data Collection, Value Stream Mapping, Simulation Modelling and Lean Interventions. The first step will be to observe the facility in running conditions to identify the means of data collection, the reasons behind the frequent or unexpected system breakdowns, maintenance schedules and frequencies, repair times, as well as possible additional support in the forms of tools or techniques that could help enhance the performance of the facility. The second step consists of developing a value stream map (VSM) showing the current state of the process in the facility including lead times, cycle times, breakdown times, and maintenance times. Meanwhile, historical data will be collected from the facility database, such as breakdown dates, maintenance times and schedule, breakdown frequency, cause of breakdown, material wait time, and individual machines' performances. In the third and last step, using the collected data, a simulation model for the facility is developed that models how the facility works in the physical world, allowing to infer the test potential improvements. This improvement would be lean interventions in the operation or structure of the system, allowing to make decisions on the operation, maintenance, and upgrades for the facility.

3.4.1. Data Collection

The data used in this study can be done in a myriad of ways. Site visits have allowed to this study's author to grasp an understanding of the operation of the facility, the function of every machine and the issues faced on a regular base by the operators. In addition to the data collected, historical data was obtained from the database of the facility, allowing for deeper understanding of the previous issues faced, adopted solutions and the impact on the system.

This historical data was standardized and cleaned, as there was a lot of duplicate entries. The data collected delves in the time of breakdown, the time the system is back to running condition, the breakdown location, the reason of the breakdown, and the average process time per machine.

3.4.2. Value Stream Mapping

Following data collection, a Value Stream Map (VSM) is developed to identify bottlenecks in the process. The VSM is created using the following four key steps.

1- define the scope and objectives by determining the process boundaries and outlining the goals, based on the study to be performed. It is crucial for the scope of the VSM to be comprehensive, though it may be limited by the availability of data. The scope should encompass the most significant steps in the manufacturing process under study and be inclusive enough to capture on-site interactions and the movement of different components.

2- collect and analyze data on the current state, including cycle times, lead times, work-in-progress inventory, and information flow, through time studies and process flowcharts.

3- Map the current state by creating a visual representation of the process flow, highlighting value-adding and non-value-adding activities.

4- Finally identifying areas of waste like bottlenecks and excess inventory, by examining activities with the longest cycle times. These activities are considered problematic for the flow of production.

3.4.3. Simulation Modeling and Validation

Succeeding the development of the Value Stream Map, Simulation Modeling is completed typically involves the following six steps:

1. Defining the Objectives: The primary objective of the simulation model is to identify areas of waste within the production flow. This objective guides the interpretation of the simulation model and its construction, based on the previously developed current state value stream map.
2. Assumptions: Clearly defining the assumptions underlying the simulation model is crucial.
3. Model Input: It is important to specify the resources available in the facility, including the various materials used to advance the production flow. The model must also account for the duration of activities, incorporating conditional conditions for waiting times for resources. Accurate data input is essential to ensure the reliability of the simulation model.
4. Verification: Checking for inconsistencies and errors in the model is necessary to ensure it accurately represents the conditions at the facility. Verification is performed using desk checking, white-box checking, and black-box checking methods.
5. Validation: Validate the model by comparing its outputs with real-world data or behaviors to ensure it accurately reflects the actual system. Here validation of the results is conducted using face validity, event validity, and historical data validity.
6. Results and Discussion: The simulation model is analyzed based on three metrics: Downtime Percentage, Total Runtime, and Total Throughput. Total Downtime is the sum of all periods when the system is not operational and cannot perform its intended functions. Downtime Percentage is calculated using the following formula shown in Equation 1:

$$\text{Downtime Percentage} = \frac{\text{Total Downtime}}{\text{Total Simulation Time}} \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \text{Equation 1}$$

Total Runtime is the period during which a program or system is executing. Total Throughput refers to the rate at which a system produces goods or completes processes over a specific period of time. The simulation model will run 150 times, this is to achieve an acceptable Standard Error, the calculation for the Standard Error can be found in Appendix A. The data obtained is collected and the average for the three metrics are calculated. On each run the model is run for the same specific period of time.

3.4.4. Lean Interventions

Lean interventions refer to the strategies, tools, and methodologies applied within an organization to implement Lean principles and practices. The primary goal of Lean interventions is to improve efficiency, reduce waste, and enhance overall value delivery to customers. These interventions are guided by the philosophy of Lean Thinking, which originated from the Toyota Production System (TPS). Lean interventions can include various activities such as process reengineering, workflow optimization, training and development, and continuous improvement initiatives (Liker, 2004).

The 14 principles of Lean, often referred to as the Toyota Way, are divided into four categories: long-term philosophy, the right process will produce the right results, add value to the organization by developing your people, and continuously solving root problems drives organizational learning. These principles serve as a comprehensive framework for implementing Lean practices in any organization (Liker, 2004).

Long-Term Philosophy

1. Principle 1: Base your management decisions on a long-term philosophy, even at the expense of short-term financial goals. Focus on creating value for customers, society, and the economy (Liker, 2004).

The Right Process Will Produce the Right Results

2. Principle 2: Create continuous process flow to bring problems to the surface. Work to eliminate interruptions and achieve smooth production processes (Womack & Jones, 2003).
3. Principle 3: Use "pull" systems to avoid overproduction. Produce only what is needed by the next step in the process, minimizing waste (Ohno, 1988).
4. Principle 4: Level out the workload (Heijunka). Work like the tortoise, not the hare. Even workloads reduce stress and increase efficiency (Liker, 2004).

5. Principle 5: Build a culture of stopping to fix problems, to get quality right the first time (Jidoka). Empower employees to stop the process to resolve issues (Liker, 2004).
6. Principle 6: Standardize tasks and processes for continuous improvement and employee empowerment. Standardized work ensures consistent and predictable outcomes (Liker, 2004).
7. Principle 7: Use visual control so no problems are hidden. Visual management tools help quickly identify deviations from standard processes (Rother & Shook, 1999).
8. Principle 8: Use only reliable, thoroughly tested technology that serves your people and processes. Technology should support people, not replace them (Liker, 2004).

Add Value to the Organization by Developing Your People

9. Principle 9: Grow leaders who thoroughly understand the work, live the philosophy, and teach it to others. Leaders should embody and promote Lean principles (Liker, 2004).
10. Principle 10: Develop exceptional people and teams who follow your company's philosophy. Invest in employee development and foster a collaborative environment (Liker, 2004).
11. Principle 11: Respect your extended network of partners and suppliers by challenging them and helping them improve. Build long-term relationships based on mutual trust and improvement (Liker, 2004).

Continuously Solving Root Problems Drives Organizational Learning

12. Principle 12: Go and see for yourself to thoroughly understand the situation (Genchi Genbutsu). Managers should go to the actual place of work to understand issues firsthand (Liker, 2004).
13. Principle 13: Make decisions slowly by consensus, thoroughly considering all options; implement decisions rapidly (Nemawashi). Involve all relevant parties in decision-making to ensure buy-in and effective implementation (Liker, 2004).
14. Principle 14: Become a learning organization through relentless reflection (Hansei) and continuous improvement (Kaizen). Regularly reflect on successes and failures to drive continuous improvement (Imai, 1986).

3.4.5. Simulation Modeling and Validation

Evaluating the various interventions involves simulating them and comparing their performance against the basic simulation model using three key metrics: Downtime Percentage, Total Runtime, and Total Throughput. It is crucial to validate the obtained results to ensure their accuracy. The conclusion will be based on identifying the solution, or combination of solutions, that performs best according to the selected metrics and Lean principles.

3.5. Evaluation

Multiple approaches will be adopted to evaluate and validate the generated model, most notably Face validity where domain experts will evaluate all aspects and outputs for correctness, while having a word during the decision making and design phase of developing the model (in this study, the SWMF operators and engineers). The second adopted approach will be the Historical Data Validation, where the existing historical data is used to first build the model and then to test the model's generated outputs and behavior. Finally, Sensitivity Analysis Validation can be adopted to test the model's behavior in certain conditions or events that have happened in the real world.

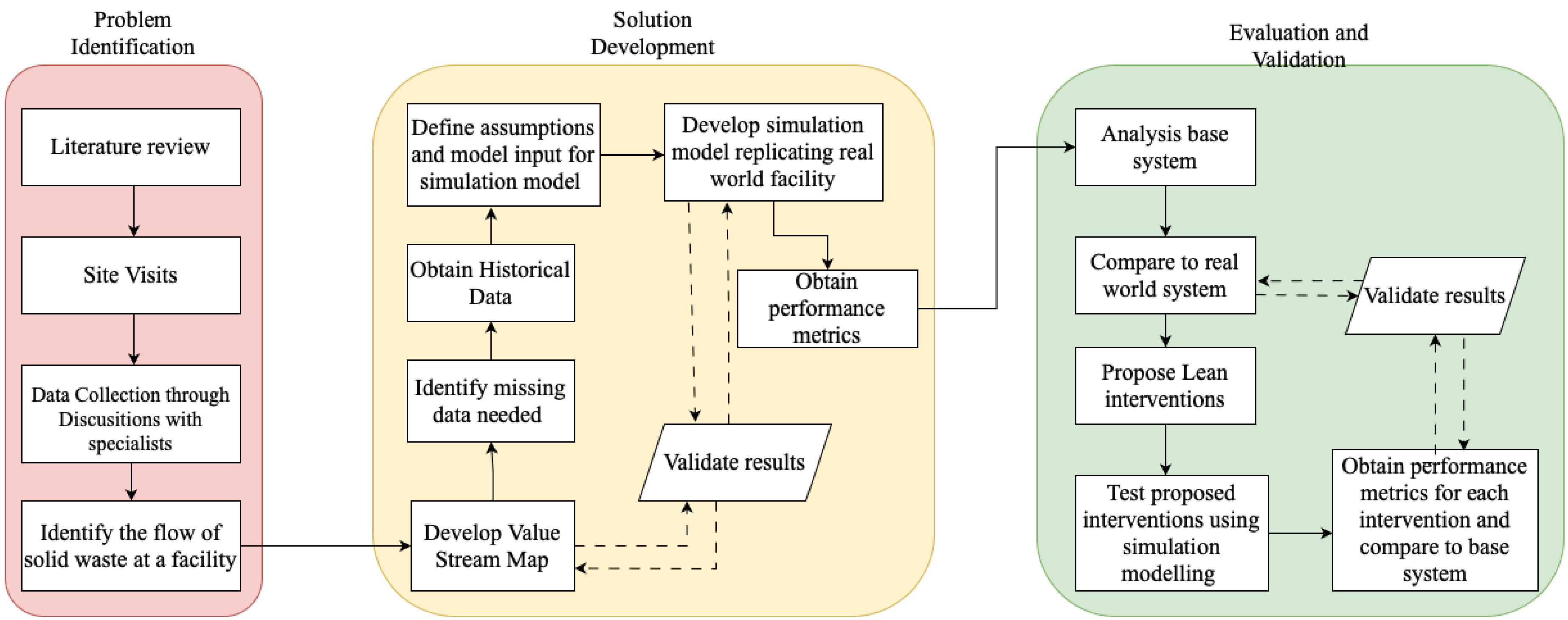

Figure 1: Research methodology

Chapter 4 – Case Study

4.1. Introduction

The solid waste management facility in this study processes about 327,000 tons of waste each year, and it's composed of the following parts: Integrated Processing & Transfer Facility (IPTF), Anaerobic Digestion Facility (ADF), Materials Recovery Facility (MRF), Waste to Biofuels & Chemicals Facility. IPTF processes a significant part of the total waste received by the SWMF, around 205,000 tons per year, it divides the waste into three categories: organic waste, biofuel production, and landfill. Organic wastes such as food residues or yard wastes found in municipal solid waste (MSW) are sent to composting unit. In the refused derived fuel (RDF) plant, the main objective of the present study, the wastes suitable for gasification are shredded and prepared to be utilized in the biofuel unit for ethanol production. The third part of IPTF sends the wastes that are not recyclable and cannot be composted or gasified to the landfill for disposal.

4.2. Process description

4.2.1 Tipping Floor

Before the start of the process, we have the tipping floor which holds the raw material. Here the waste trucks dump the MSW on the floor, as seen in figure 2, and exists the building.

Figure 2: Truck Dropping MSW at Tipping Floor

There are three steps that take place once the MSW arrives at the facility; first, the waste is collected into a big pile, as seen in Figure . Using a crane, step 2 is airing the waste to ensure it is loose and not in clumps; this step also allows the crane operator to identify any large items that will cause damage to the machines, such as big metals, white waste, or furniture. The final step is to start the processing of the MSW; the waste bags are put into bag backers, which will take the waste to the next phase of the process, the Pre-Processing Facility.

It is important to mention that during the seasons where the waste will fluctuate in volume, once the capacity of the facility is reached, the MSW that arrives to the facility is directly diverted to landfills without being processed.

Figure 3: Tipping Floor

4.2.2. Pre-Processing Facility

The Pre-Processing facility at the solid waste management facility plays a crucial role in sorting and preparing waste for further processing. This facility handles garbage, food scraps, and recyclables collected from the city homes, ensuring that materials are appropriately processed for recycling, composting, or conversion to energy. The Integrated Processing and Transfer Facility, a key part of the SWMF, specifically sorts waste to remove recyclables and compostable materials, enhancing the efficiency of waste management operations in the city.

The PPF undertakes several key steps to prepare waste for further processing:

1. Initial Sorting: Waste materials are sorted to separate recyclables, compostables, and non-recyclables.
2. Material Separation: Advanced sorting technologies remove metals, plastics, and other recyclables.
3. Shredding and Grinding: Waste materials are shredded or ground into smaller pieces to facilitate further processing.
4. Screening: Materials are screened to remove contaminants and ensure proper sizing.
5. Transportation: Sorted and processed materials are then transported to appropriate facilities for recycling, composting, or energy conversion.

The PPF comprises two parallel lines that are fed by a grapple. The raw municipal solid waste (MSW) is transferred from the tipping floor via a hopper and conveyors to the first hand-sorting room, where workers manually remove hazardous household waste and bulky items. Following this manual sorting, the remaining waste undergoes mechanical size separation using a two-stage trommel and a disc screen, which divides the waste into different streams for further processing. The first and second stages of the trommel have aperture diameters of 5 cm (2 inches) and 23 cm (9 inches), respectively. Following the second stage, a disc screen with a cut-off size of 12.7 cm (5 inches) further separates the waste materials. Waste materials larger than 23 cm (9 inches) exit the trommel as oversized flow (overs) and are subject to secondary hand-sorting. The described PPF is illustrated schematically in Figure 4 (Rajabpour, 2019).

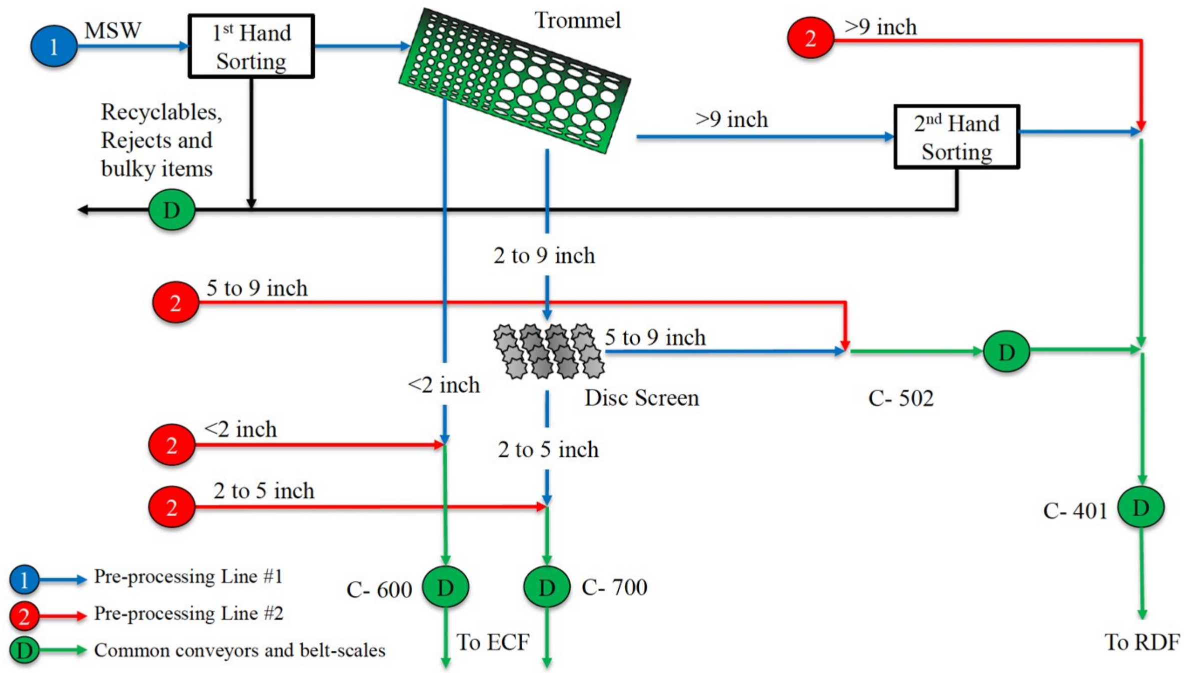

Figure 4: PPF Process

The scope of this research will only include the waste going through the first sorting room, the trommels, and the second sorting room. The material obtained from the disc screens will be considered to be 2 to 5 inches in size.

After completing the secondhand sorting, the remaining waste is on the conveyor belt, goes to the RDF facility, and is dropped on the floor.

4.2.3. Refused Derived Fuel

After completing the secondhand sorting of the PPF, the remaining waste on the conveyor belt goes to the RDF facility and is dropped on the floor, where it will wait until the beginning of the RDF process, as seen in Figure 5. The first step of the RDF processing is the infeed pit, where a bulldozer operator will feed the waste into the machine, which will be transported by a conveyor belt to a pre-shredder, turning the waste to a size smaller than 75 mm. This is followed by a ferrous separator, which will remove all ferrous metals by using a magnet belt hanging above the conveyor. Until this point, a single line of equipment is present; from now on, two identical parallel lines are present, which can be run simultaneously or individually. The following station is a waste screen or waste shaker bed, which will take out all elements that are smaller than 25 millimeters; the interior can be seen in Figure 6. This is followed by a wind shifter where a current of air will pick up light materials (such as paper and cardboard) and move them to the next step, whereas heavier materials will drop and be discarded into a bin. The last separation step is an eddy current machine where non-ferrous metals, unwanted in the final product, will be removed. The last processing step is the re-shredding of the remaining materials, taking them to a size of 50 millimeters, and then transporting them to another facility. It is important to note that material being transported between machines is done continuously and done through conveyors. The described RDF is illustrated schematically in Figure 7.

Figure 5: Inventory of Waste on the RDF Floor

Figure 6: Inside the Waste Screen

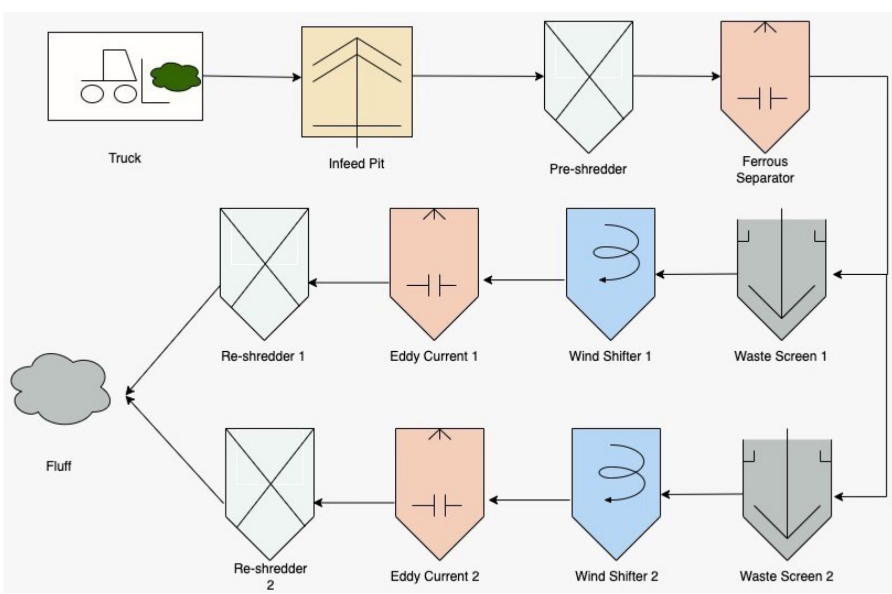

Figure 7: Process flow diagram of RDF plant

4.3. Facility Database

The facility tracks downtime, this data includes the time of start of downtime, the time the facility is back to running condition or end of downtime, the cause of the downtime, and the machine related to the downtime. It is important to note that this data is collected through a spread sheet that is manually filled in by the operator, with no standard terminology used for causes of the breakdown. Another set of data was obtained, which represented the average process time for each machine, with the machine specifications.

Chapter 5 – Value Stream Mapping

5.1. Introduction

Value Stream Mapping (VSM) is a vital lean management tool used to visualize, assess, and optimize the flow of materials, information, and activities within a process or value stream. Rooted in Lean Thinking and Lean Six Sigma principles, VSM provides a comprehensive overview of the process, from raw materials to end-product delivery, enabling organizations to identify and eliminate waste, streamline operations, and enhance overall efficiency (Rother & Shook, 2003).

The primary objective of VSM is to distinguish value-adding (VA) activities from non-value-adding (NVA) activities and necessary but non-value-adding (NNVA) activities. This allows organizations to optimize value-adding steps while minimizing inefficiencies such as overproduction, waiting times, excessive inventory, unnecessary transport, and rework.

VSM involves creating a visual representation of the value stream, encompassing material flow, information flow, and timelines. This detailed map aids in waste reduction, lead time reduction, and improved collaboration (Rother & Shook, 2003).

Key Benefits of Value Stream Mapping

1. Waste Reduction: Identifies and eliminates waste, leading to better resource allocation and cost savings.
2. Process Optimization: Pinpoints bottlenecks and delays, reducing lead times and enhancing customer satisfaction.
3. Enhanced Collaboration: Promotes cross-functional teamwork and data-driven decision-making, fostering continuous improvement.
4. Customer Focus: Provides insights into processes from the customer's perspective, facilitating more customer-centric operations.
5. Increased Efficiency: Improves productivity, enabling organizations to achieve more with fewer resources.
6. Versatility: Applicable across various industries and processes, making VSM a valuable tool for continuous improvement (Womack, Jones, & Roos, 2007).

In conclusion, Value Stream Mapping is an essential lean management tool that offers organizations a comprehensive view of their processes. By enabling waste reduction, lead time reduction, and improved efficiency, VSM fosters operational excellence and continuous improvement through collaboration, data-driven decision-making, and a customer-centric approach.

5.2. Value Stream Map

The Value Stream Map presented in this chapter pertains specifically to the city Waste Facility's RDF process, starting from the Pre-Shredder to the completion of process at the Re-Shredder.

This map was developed using data collected during the multiple visits of the facility and the discussions with personnel. Initially, the study considered including the Customer demand, but this was excluded due to the variability in the operation of the client's facility. It is also important to note that, there is no inventory between the different stages of the process, as the machines are connected through conveyors, each batch moves to the next stage before a new batch is taken from the stage upstream.

The Value Stream Map was refined through multiple site visits, with revisions made as the processing steps became clearer. Feedback from one of the engineers on site and the use of historical data was crucial to determine the average cycle time for each machine.

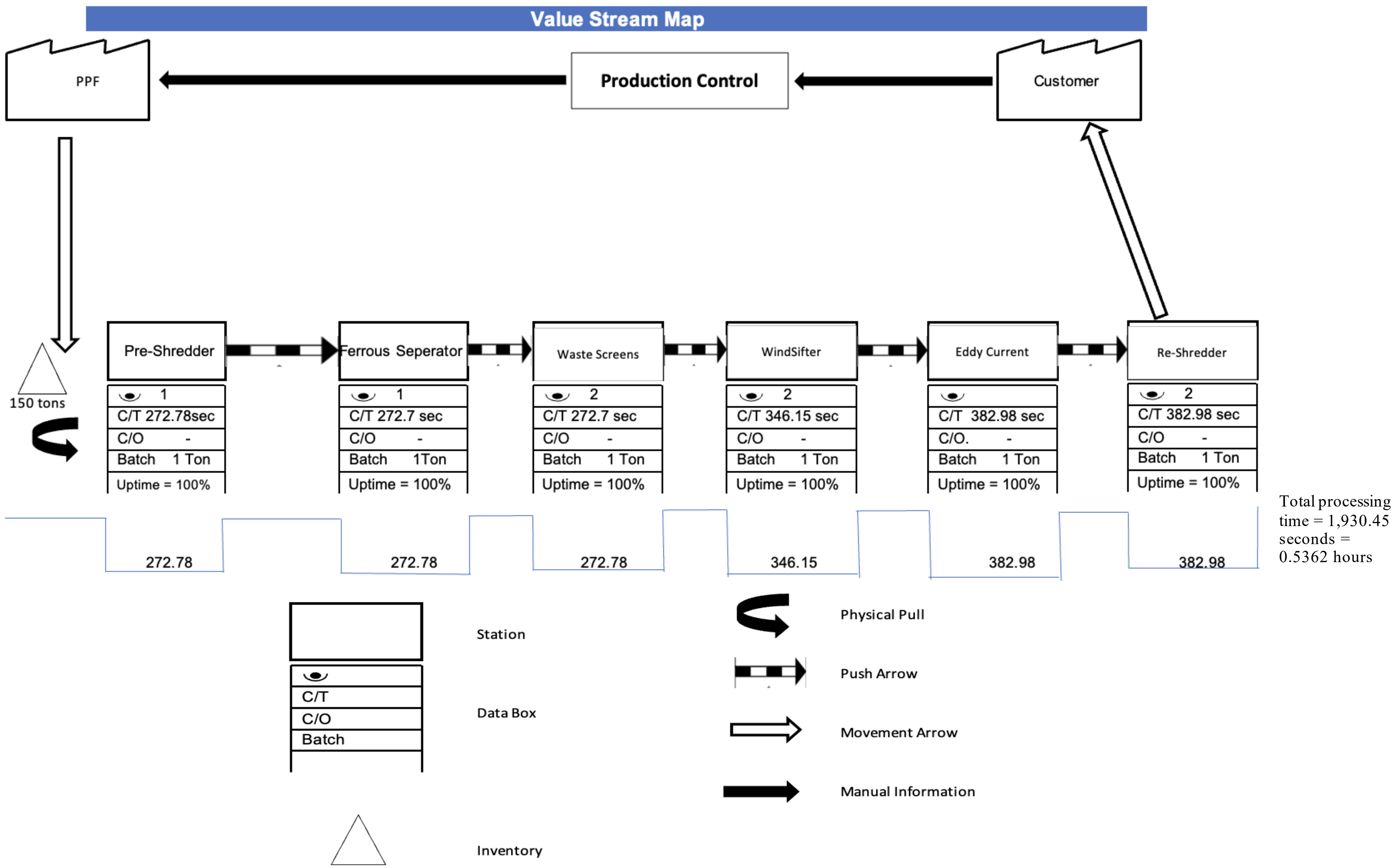

Figure 8: SWMF Value Stream Map

5.3. Validation

The Value Stream Map was validated by the engineers from the facility after its development, who confirmed the data collection and subsequent steps. The steps depicted in the Value Stream Map represent the actual procedures followed at the RDF. The engineer verified the processing duration of various machines. Additionally, the engineer confirmed the logical flow of the steps outlined in the Value Stream Map. This map provides a view of the different processes the solid waste going through at the RDF to obtain the final product, enhancing our understanding of the facility operation for further analysis.

5.4. Validation

The development of the Value Stream Map provides a detailed picture of the steps involved in the processing of MSW at the RDF. This map helped identify several deficiencies in the process. The conclusions drawn from the Value Stream Map include:

1. Production is influenced by client's operation and breakdown, which is beyond the scope of this study.
2. A significant amount of time is spent on maintenance and repairs of the machines.
3. Additional analysis using simulation modeling is needed assess current production of the facility.

The Value Stream Map serves as a foundational tool for Simulation Modeling, which aims to analyze the base case of the IPTF. This modeling assesses throughput and downtime percentage. Additionally, Simulation Modeling is used to test proposed lean interventions aimed at reducing downtime and repair time to increase the production output.

Chapter 6 – Simulation Modeling

6.1.Introduction

Computer simulation is recognized as a crucial adjunct to traditional engineering analysis methods, providing significant advantages in understanding and managing complex systems (Clark et al., 2007). It plays an essential role across various sectors by offering deep insights into intricate processes, aiding decision-making, and mitigating potential risks. By developing virtual models of real-world scenarios, simulation allows for safe experimentation, enabling researchers, engineers, and policymakers to explore different strategies and outcomes efficiently without the associated real-world consequences.

In manufacturing, simulation optimizes production processes, leading to enhanced efficiency and reduced costs (Banks, 2005). In healthcare, it improves patient care and operational workflows by modeling patient flow and treatment protocols (Law & Kelton, 2007). Transportation logistics benefit from simulation through better route planning and resource allocation, ultimately leading to more effective and sustainable systems (AnyLogic, n.d.).

Moreover, simulation is invaluable for scenario analysis, helping organizations anticipate and prepare for unexpected events and disruptions. This capability is critical in today's dynamic and uncertain environment, where the ability to quickly adapt to changes can determine organizational success. By facilitating the testing of hypotheses, validation of designs, and prediction of outcomes, simulation supports not only operational efficiency but also strategic innovation and resilience (Sokolowski & Banks, 2010).

The influence of simulation extends beyond traditional research and development into areas such as policymaking, resource allocation, and strategic planning. By embracing simulation methodologies, organizations can enhance their decision-making processes, improve resource utilization, and foster a culture of continuous improvement and innovation. This broad applicability and the ability to generate actionable insights underline the indispensable role of simulation in modern engineering and management practices.

In this chapter, simulation modeling is utilized to analyze the current state of throughput, runtime and downtime, and identify potential lean improvements based on the results. The chapter outlines the methodology used to develop the simulation model, including its verification and validation processes. Additionally, the chapter discusses and explains the findings derived from the model.

6.2. Simulation Objectives

Prior to constructing the simulation model (SM), objectives are established and serve as a guiding framework for customizing and adjusting the model. The primary aim of the model is to achieve the specified objectives in a straightforward yet effective manner that aligns with its intended purpose. The following are the set objectives:

- Replicate the real-world solid waste processing facility through a simulation model that can be used to investigate different scenarios, and
- Develop and validate a set of lean interventions that are aimed to reduce downtime, and repair time to increase the production output.

6.3. Assumptions Undertaken

The following assumptions are derived from observations made during the study:

1- One batch will be processed at a time per machine, with each being 1 ton in weight, for simplicity. With every batch being identical in composition, the variability of the composition MSW is not modeled in this study.

2- Only one of the parallel lines in the RDF will be utilized at the same time, both lines will not be running at the same time, as to replicate the approach the operations team have adopted at the EWMC, furthermore, after each breakdown the line will switch.

3- The data is limited on breakdown times and frequencies of individual machines to find the distributions; to find a distribution that can be modeled and avoid the use of deterministic values, a breakdown of the entire facility will be modeled using the data of all the machines, where the entire system will shut down until the repair/maintenance is completed.

4- All downtime in the model is due to breakdowns, no outside factors is modeled here, such as lack of MSW or the Client not requesting the product. The Client here is the entity taking the final product.
5- The dependences between the different elements are not considered when it comes to the breakdowns, hence if one machine is not functioning properly it won't affect the other machine's breakdown probability.

6.4. Model Input

The IPTF process comprises 12 steps, which are the basis of the developed simulation model. Each step is represented by a task with a specific duration. This approach ensures that the objectives and assumptions outlined earlier are met. As mentioned previously, limited data is available on the operation of the machines and there processing time, the only available data, is the average run time provided by the engineers from the facility. To avoid a deterministic approach and be able to model a more realist simulation, for the process time of each machine, a triangular distribution was adopted, where the average value served as the mode (most likely value). One common approach is to set the value to 10% away from the most likely value. (Podlasek, 2022). Hence, the minimum and maximum values of the triangular distributions are at a 10% margin from the mode.

Using a triangular distribution in simulation modeling allows to avoid infinite loops as it is bound, providing a defined range of possible values with a known minimum, maximum, and most likely value. This ensures that the simulation does not get stuck in an endless cycle of improbable values. The triangular distribution is simple to implement and useful in scenarios with limited data, offering a reasonable approximation of uncertainty and variability (Law & Kelton, 2007; Vose, 2008).

Table 1 represents the distributions of the processing time for each machine, those distributions were found using the average time found using the data base obtained from the facility management team, this data base was collected over 25 months. As for the mode of the triangular distribution and taking 10% away from this value as the minimum and maximum of the range. Using the Pre-shredder as an example, the average process time found in the historical data showed to be 272.73 seconds for every batch of 1 ton, the minimum and maximum were found using the following formulas :

$$\text{Minimum} = \text{Average Process Time} * (1 - 10\%) \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \text{Equation 2}$$

$$\text{Minimum} = 272.73 * 0.9$$

$$\text{Minimum} = 245.457 \text{ seconds}$$

$$\text{Maximum} = \text{Average Process Time} * (1 + 10\%) \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \text{Equation 3}$$

$$\text{Minimum} = 272.73 * 1.1$$

$$\text{Minimum} = 300 \text{ seconds}$$

Hence, the distribution for the processing time of the Pre-Shredder is : Triangular(245.457,300,272.73), following the form of Triangular(Minimum, Maximum, Mode).

Table 1: Processing time distribution of the step in the process (in seconds)

Process	Processing time distribution (in Seconds)
Move in Crane (tipping floor)	triangular(240, 300, 100)
Bag breaker	triangular(60, 100, 60)
Hand sorting Room 1	triangular(90,110,100)
Trommel	triangular(65,79,72)
Hand sorting Room 2	triangular(90,110,100)
Move in bulldozer (RDF floor)	triangular(198,242,220)
Pre-shredder	triangular(245.457,300,272.73)
Ferrous Separator	triangular(245.457,300,272.73)
Waste Screen	triangular(245.457,300,272.73)
Wind Shifter	triangular(311.535,380.765,346.15)
Eddy Current	triangular(344.682,421.278,382.98)
Re-Shredder	triangular(344.682,421.278,382.98)

According to the literature, the probability of breakdown increases with the increase of runtime due to the cumulative wear and tear on machinery components. As machines operate for extended periods, their parts are subject to ongoing stress and degradation, leading to a higher likelihood of failure (Bertsche, 2008; Dhillon, 2002). This relationship is often modeled using reliability engineering principles, which show a correlation between increased usage and the rising failure rate. Using the historical data collected from the facility, five categories of breakdown probability can be identified when calculating the time between breakdowns.

Table 2 represents the Runtime Ranges with the according probability of breakdown, the range was found by listing the runtime between breakdowns and then identifying the ranges, 5 ranges were identified, then finding the total number of breakdowns taking places within those ranges, and then diving those numbers by the total number of breakdowns. Then the cumulative probability can be calculated to find the probability of breakdown. This approach was adopted due to the lack of data to model this probability, as nature is smooth and this approach is abrupt, here with every range the probability jumps up to a fixed value, as it needs to represent the relation between time and probability of breakdown, with the increase of runtime, the probability of breakdown increases.

Table 2: Probability of Breakdown Ranges

Runtime Range in Hours	Probability of Breakdown
0 to 99	0.00
100 to 299	0.3125
300 to 499	0.5313
500 to 999	0.7188
Over 1000	1.00

As for the Repair time, the time spent to bring the facility back to running conditions, 3 levels can be defined, the first one is Cleaning and Small Maintenance, where the maintenance crew will have to deal with regular maintenance such as replacing the blades of the pre-shredder or cleaning the wind sifter and shaker bed, usually will not exceed the 10 hours and can be tackled within the same workday or before the start of the next workday, usually will not exceed the 10 hours. The second level is Repairs, which requires a little more investigation and parts, ranges between the 10 to 20 hours. The Final Level is Major Upgrades, here it is for big repairs which require more time, or for planned changes in the facility that will take anywhere between a couple days and a couple weeks.

The ranges were defined with the help of a field expert, then using historical data the modes of the triangular distributions were identified, by sorting the breakdown times in increasing order, identifying the previously selected ranges, and finally finding the mode, the minimum and the maximum of each range.

The triangular distribution for the three levels can be found in table 3 below.

Table 3: Repair Time Distributions

Level	Distribution (in Hours)
Cleaning and Small Maintenance	Triangular (2,10,5)
Repairs	Triangular (10.5,20,15)
Major Upgrades	Triangular (20.5,209,47.26)

6.5. Simulation Model

The simulation model shown in Figures 9, 10 and 11 was built on Any Logic, each batch of solid waste is going through the ten steps of processing. Parts of the facility include a second identical parallel line, the one in the RDF will not function at the same time. The batch of 1 ton will follow the process explained previously, until reaching the final stage at the re-shredder.

A source block is introduced at the beginning of the process, which represents the waste collection trucks that bring the MSW to the facility, it is dropped on the tipping floor, before it is introduced to the process, starting with the bag breakers, both lines are fed simultaneously and equally, going to the firsthand sorting room to remove bulky items, then the trommel and finally the second sorting room. The product is then dropped on the RDF floor, here a second source block was added to ensure the RDF which provides 100 tons, this is to represent the inventory of solid waste that is always present on the RDF floor, to make sure the facility will always have materials to process.

On entry to the infeed pit, the material will go through the Pre-Shredder, then the ferrous separator, before moving to the parallel lines, as mentioned in the assumptions, these two lines will not function at the same time, waste screens are the first step, then the wind sifter, the eddy current and the re-shredder. The process of delivering the product to the customer is not modeled here, as it falls outside of the scope of this study. An event element was added in this model, it will check for breakdowns by associating a breakdown probability to the current runtime since the last breakdown, as seen in Table 2.

Stop blocks were included in the model before every step, to have control over the flow of the batch, when a breakdown takes place, we are able to stop all elements, this is a crucial step to replicate the real-world model.

Multiple metrics are derived from the discrete event simulation model illustrated in Figures 9,10 and 11. The foremost metric obtained is downtime %, the total runtime and the throughput, which are based on the assumptions established during the development of the simulation model. These metrics serve as a benchmark for evaluating and comparing potential lean interventions.

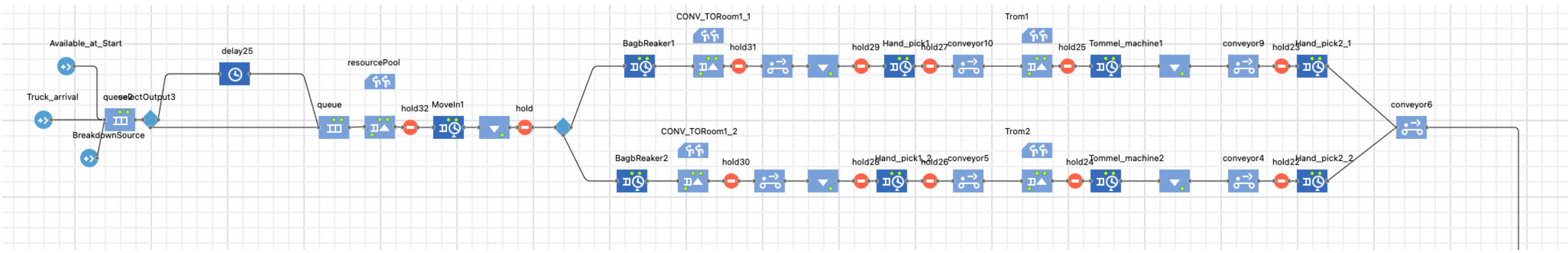

Figure 9: IPTF Base Simulation Model part 1

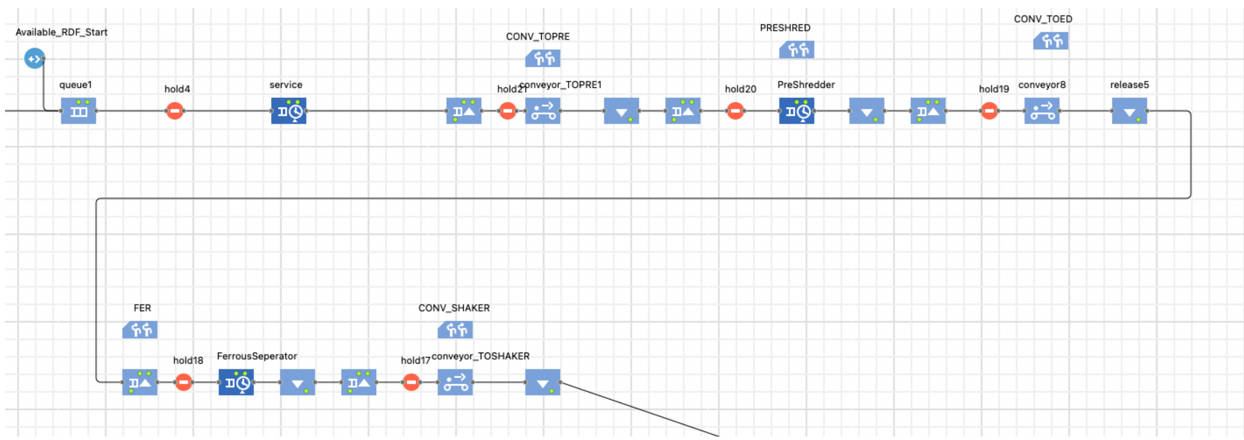

Figure 10: IPTF Base Simulation Model part 2

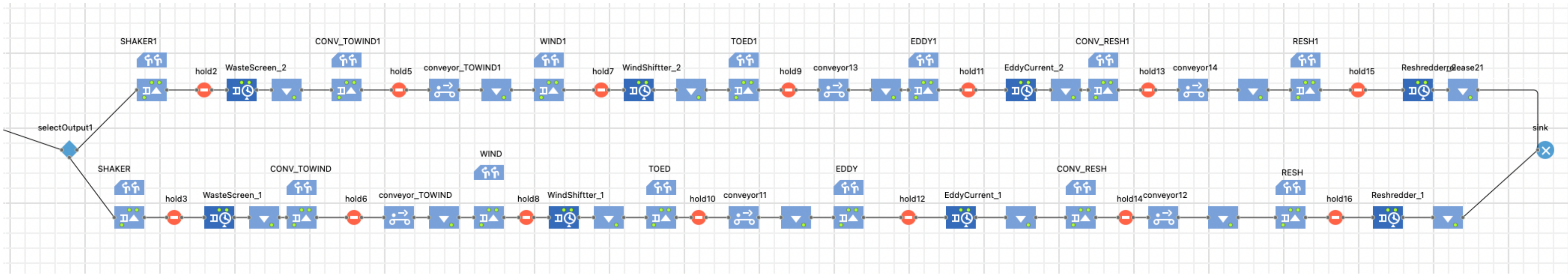

Figure 11: IPTF Base Simulation Model part 3

6.6. Verification

The simulation modeling adopted in this study are aligned with the methodology developed by Sargent (1992). The initial phase involves defining the system under study as a problem entity. This entity is then translated into a conceptual model, followed by its transformation into a computerized model in the final step. Figure 12 presents the processed defined by Sargent (1992).

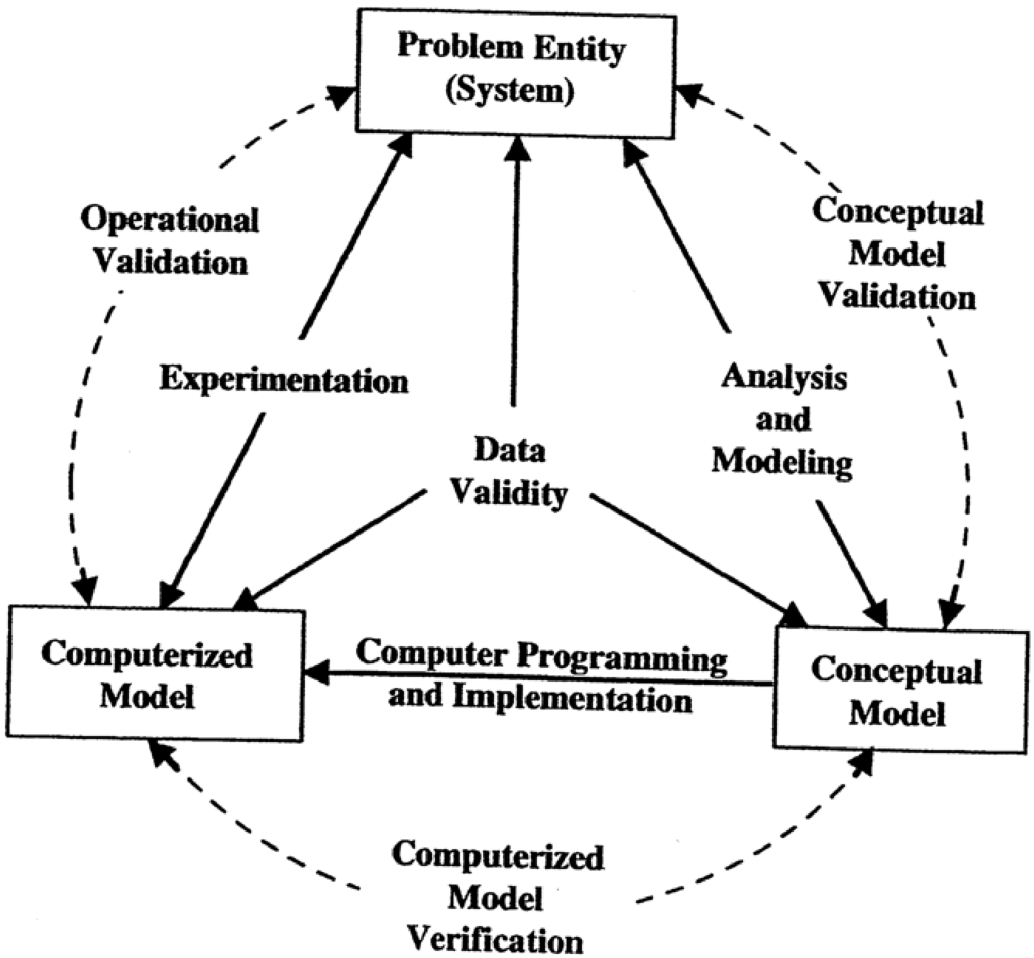

Figure 12: Simulation Modeling process (Sargent, 1992)

After the creation of the simulation model, to assure its accuracy in reflecting real-world conditions it must be verified. The discrete event simulation model built in this study is based on the validated Value Stream Map discussed in chapter 5 and mirrors the actual processed the MSW goes through at the IPTF. Several verification techniques are outlines by Balci (1994) for simulation modeling, including desk checking, white-box testing, and black-box testing.

6.6.1 Desk Checking

This technique involves investigating the logic and consistency of the model. The logic is clear and direct; there is a single, definitive path for the MSW to be processed. It needs to go through every machine in the order, there is no way to introduce it at a random point in the line.

The simulation model was reviewed with field experts, who evaluated its logic and alignment with real-world solid waste management practices. The verification process focused on the progress of a MSW through the model, ensuring no redundant steps were included and that the correct values were used at conditional nodes. The linear and straightforward nature of the model ensures that a batch progresses through the simulation without repeating steps.

6.6.2 Black-Box Testing

Black-box testing compares the simulation model's inputs and outputs without considering the internal processes. Various input scenarios were tested to observe the model's behavior. In this study, output obtained after running the model for a specific period of time, with controlled breakdown times. The output matched the input values and production rate, verifying the model's accuracy.

6.6.3 White-Box Testing

White-box testing examines the interactions between elements within the simulation model, and not only what the system produces. Given that the objective is to assess current state of production of the facility, it is crucial to ensure the proper interaction of different elements. The simulation tracks batch moving from one machine to another. The batch in the system undergoes all necessary steps and conditional nodes before being recorded. The number of batches processed was verified by counting entities at each machine throughout the production process. This count was consistent and matched the total number of batches within the system. Another approach was tracking the change in weight for each batch going through each machine, as the data obtained from the facility showed how each machine would eliminate unwanted materials from the MSW passing through the RDF. Figure 13 was obtained from the management team at the EWMC, it represents Mass Balance of the batch in the RDF, with the percentage of the waste being eliminated at each station.

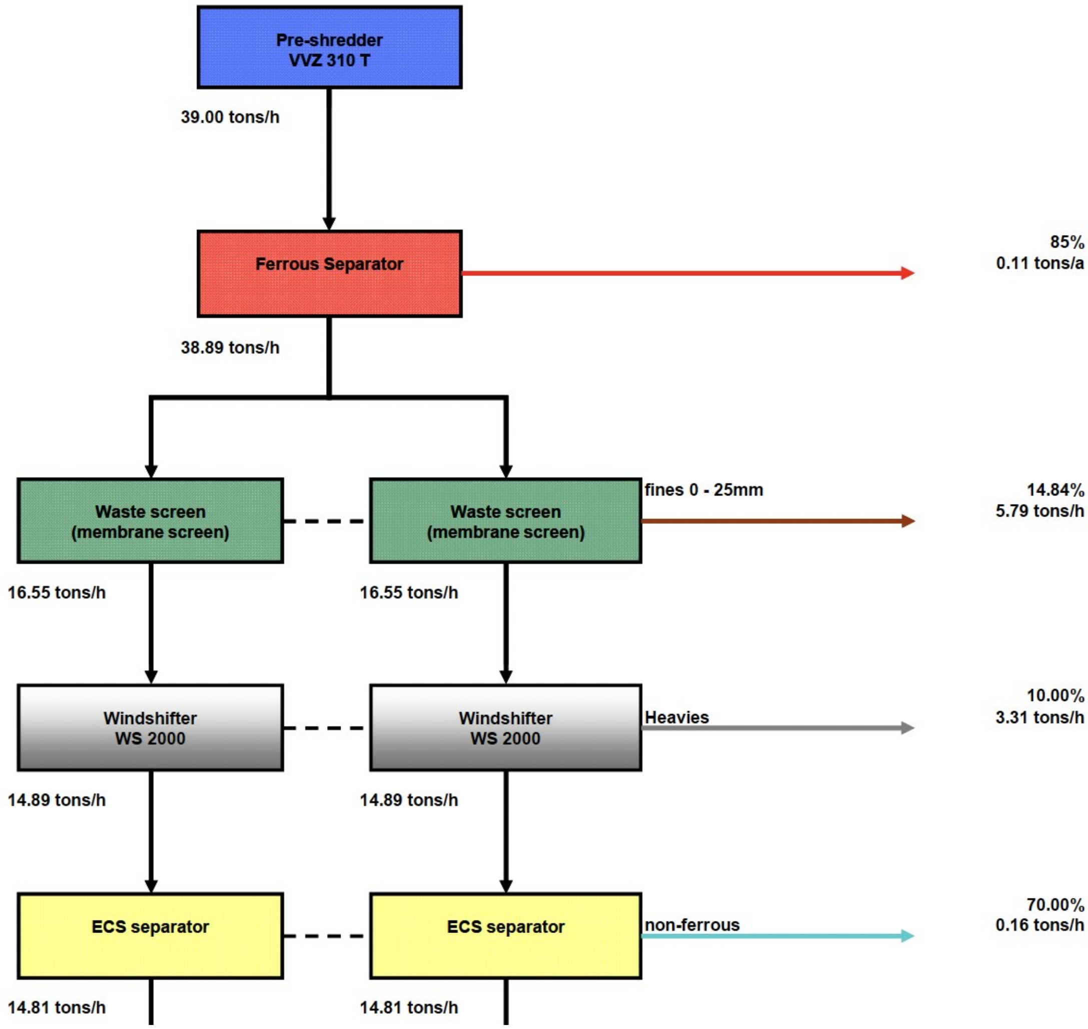

Figure 13: Mass Balance of RDF

The facility engineer confirmed the coherence of interactions between different elements, ensuring the robustness and reliability of the developed simulation model.

6.7. Validation

Validation ensures that the model accurately represents the real-world system according to its objectives. Validity pertains to the model's practical applicability and effectiveness (Landry et al., 1983). In this study various techniques based on Sargent (2010) were employed, to confirm that the correct model was constructed. These included Face Validity, Historical Data Validation, and Sensitivity Analysis Validation.

6.7.1 Face Validation

Face validation involves ensuring that a simulation model's logic and output appear reasonable to experts familiar with the real-world system. It relies on qualitative assessments from these experts to judge whether the model's behavior and assumptions are consistent with their understanding of the actual system (Law & Kelton, 2007; Sargent, 2010). This step is crucial for establishing the model's credibility and acceptance among stakeholders.

During the face validity process, the model's results, specifically the average tonnage produced per hour, were validated by comparing them to the machine with the lowest productivity. The simulation model was reviewed with field expert from the facility, who confirmed that the results accurately reflected the facility. Additionally, any questions or ambiguities were addressed and incorporated into the model, which was iteratively updated to ensure accuracy.

6.7.2. Historical Data Validation

Historical data validation is a technique used to verify a simulation model by comparing its outputs with real-world data from past operations. This process involves using historical data to ensure that the model accurately reflects the behavior of the system being studied. According to Law and Kelton (2000), this method helps to establish the credibility of the model by demonstrating that it can replicate known outcomes. Sargent (2010) also emphasizes that historical data validation is crucial for ensuring that the model can reliably simulate future scenarios based on past performance.

During the historical data validity process, the model's results, specifically the throughput, the average downtime per breakdown, were used to ensure that the model accurately reflects the behavior of the system being studied. The simulation model’s output was validated by taking the duration in hours set for the simulation model to run and multiplying it by the average output obtained from historical data, 9.4 Tons/Hour. This number was then compared with the output obtained from the model.

6.7.3. Sensitivity Analysis Validation

Sensitivity analysis validation involves assessing the robustness of a simulation model by evaluating how variations in input parameters affect the model's outputs. It helps identify which parameters significantly influence the results and ensure that the model reliably reflects real-world scenarios under different conditions. According to Saltelli et al. (2008), sensitivity analysis validation is crucial for verifying that the model responds appropriately to changes in key inputs, thereby enhancing its credibility and reliability. Pannell (1997) and Hamby (1994) also emphasize that this process supports the identification of critical parameters, guiding effective model calibration and refinement.

Variating the probability of breakdown of the system, allowed to analyse the system and obtain different downtime %, showing a consistent variation in production based on the percentage of downtime. For every 1% the downtime moved, a change of about 389 tons in production was observed. These results were validated by field expert and compared to historical data, confirming the model reliably reflects real-world scenarios under different conditions.

6.8. Results and Discussion

The simulation model was executed 150 times over a period of 3600 hours using AnyLogic, to achieve precise insights into the system's behavior. This comprehensive run allowed us to analyze the performance of different machines within the facility. The validated outcomes served as a foundation for proposing lean interventions. These interventions were then simulated to evaluate their overall impact on the system and production. Key metrics such as Downtime percentage, Total Runtime, and Total Throughput were derived from the simulation model, their average values from the 150 runs were calculated, the result are discussed in detail in the subsequent sections of this chapter.

6.8.1. Total Throughput

The model is run over a period of 3600 hours, assuming that every workday has 10 hours. Hence each run will represent the production over almost 1 year, reflecting the behavior and the condition of the system over a long period of time.

Figure 14 represents the throughput for the 150 runs conducted for the model over a period of 3600 hours. The throughput here ranges from 21,984.49 to 29,634.93 tons, with a mean of 26,099.88 tons, and 1,879.56 as a standard deviation. Compared to the current facility throughput, which is around the 26,452.15 tons, hence the model runs on par with the collected data of the facility.

Running the model at ideal conditions, with no breakdowns, over the same period of time of 3600 hours, the model produces an average of 33,840 tons. Hence a 22.87% difference in production between ideal condition and our base model.

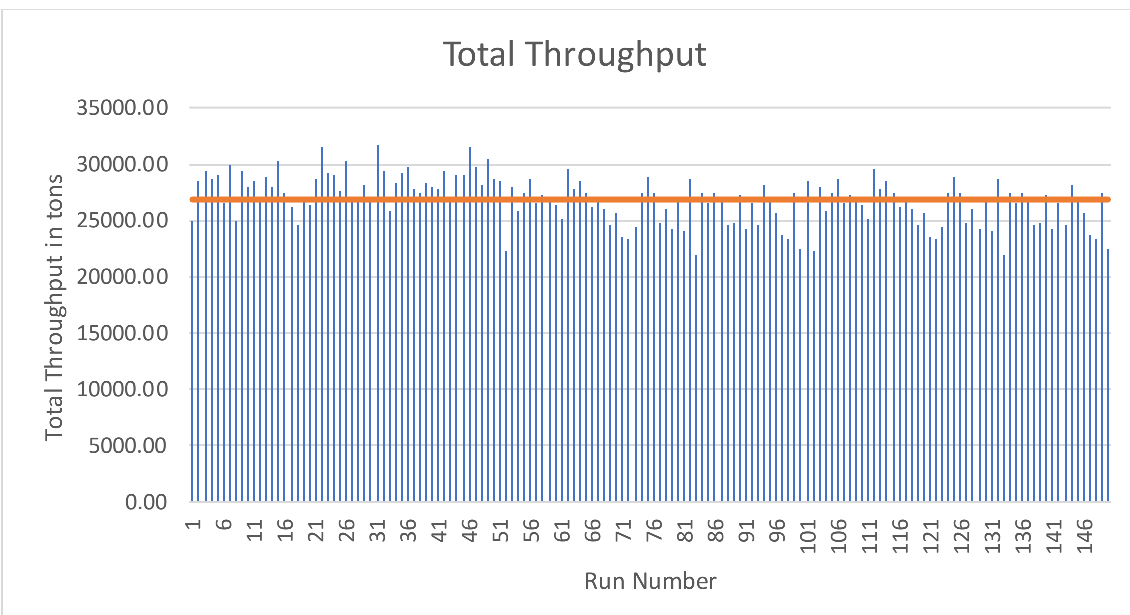

Figure 14: Throughput of the 150 runs (Base Model)

6.8.2. Downtime percentage

The total downtime is first obtained from the model for the runs, collecting every second the entire facility is not operational within the 3600-hour simulation period. Hence each run will represent the total downtime over almost 1 year, reflecting the behavior and the condition of the system over a long period of time.

Figure 15 represents the Total Downtime for the 150 runs conducted for the model over a period of 3600 hours. The downtime here ranges from 296.23 to 1117.77 hours, with a mean of 674.35 hours, and 198.96 as a standard deviation. The average downtime percentage comes out to be 18.73%, which compared to the current state of the facility, it is facing downtimes of almost 17.82%, which run on par with the results obtained in the simulation model.

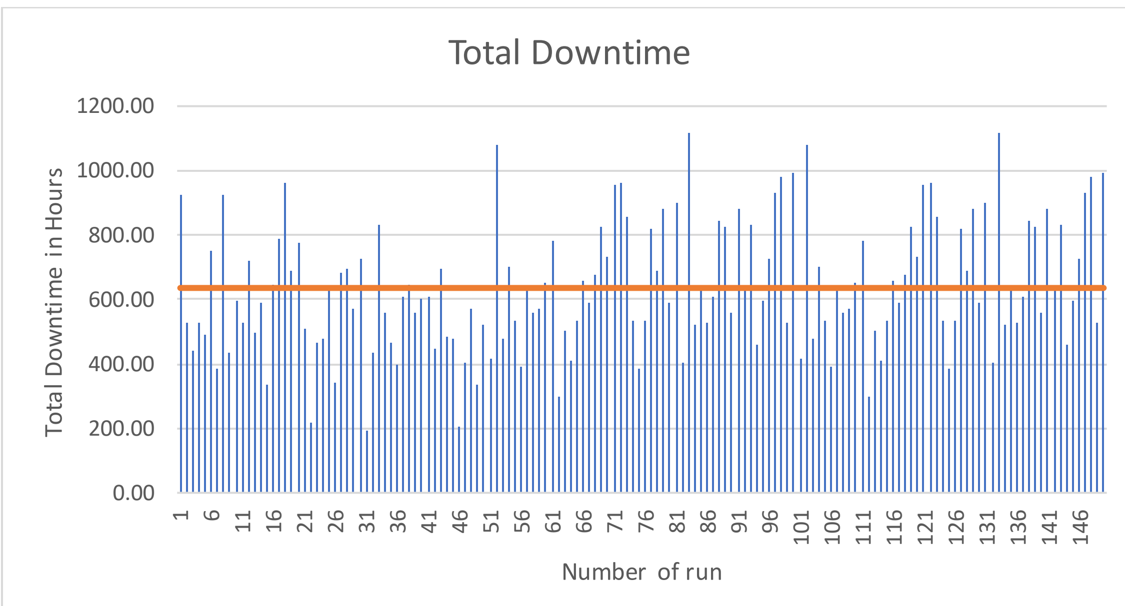

Figure 15: Total Downtime of the 150 Runs (Base Model)

6.8.3. Total Runtime

The total runtime is obtained from the model for the runs, collecting every second the entire facility is operational within the 3600-hour simulation period. Hence each run will represent the total runtime over almost 1 year, reflecting the behavior and the condition of the system over a long period of time.

Figure 16 represents the Total Runtime for the 150 runs conducted for the model over a period of 3600 hours. The runtime here ranges from 2482.23 to 3303.77 hours, with a mean of 2925.65 hours, and 198.96 as a standard deviation.

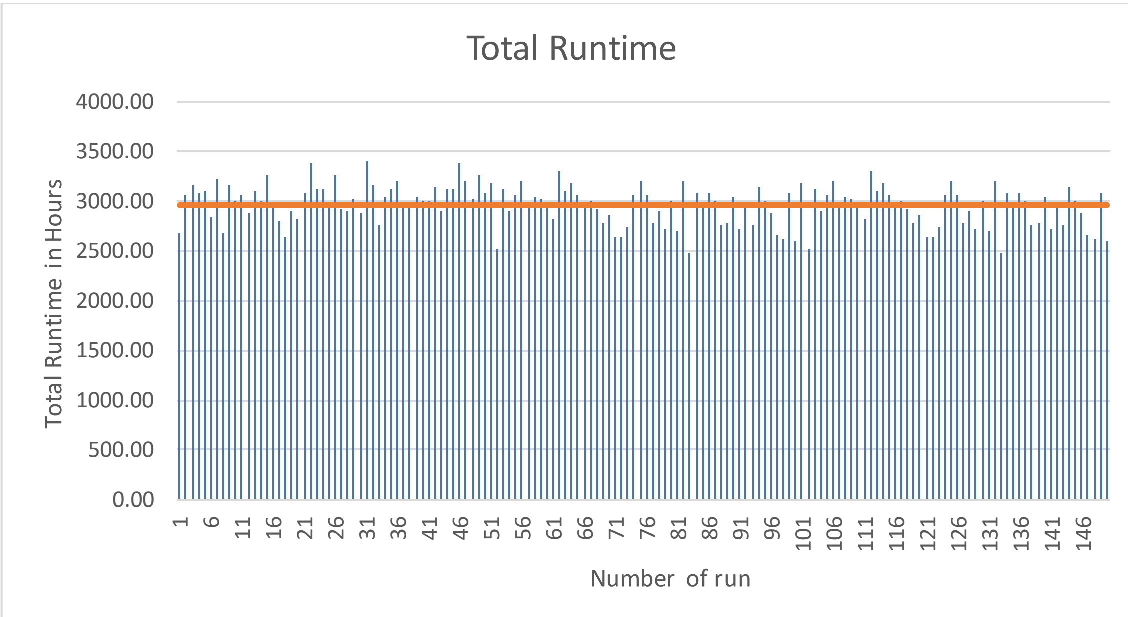

Figure 16: Total Runtime of 150 Runs (Base Model)

Table 4 below displays a summary of the key metrics collected for the base model.

Table 4: Summary of metrics for base model

	Output Tonnage	Total Downtime (hours)	Total Runtime (hours)
Mean	26099.88	674.35	2925.65
Stand Div.	1879.56	198.96	198.96
Min	21984.49	296.23	2482.23
Max	29634.93	1117.77	3303.77

In addition to a downtime percentage of 18.73%.

These metrics serve as a benchmark for evaluating and comparing potential lean interventions in the next chapter. As the downtime percentage is less than 1% away from the real-world data collected from the facility (17.82% vs 18.73%), as for the total throughput it is 1.34% away.

6.9. Conclusion

In this chapter the process of modeling the Solid Waste Management Facility was discussed. It covers the objectives that the simulation model (SM) was designed to achieve, and the assumptions made beforehand. Additionally, it describes various techniques used for model verification and validation. Verification methods include desk checking, black-box testing, and white-box testing, while validation methods encompass face validity, event validity, and sensitivity analysis validity. The outcomes of the model are aligned with the initially defined objectives, focusing the following metrics downtime %, total runtime, and total throughput. Chapter 6 goes over the lean interventions and their impact.

Chapter 7 – Lean Interventions

7.1.Introduction

A thorough analysis of the existing process is essential for identifying ways to enhance the system through lean principles. It's important to understand that change can only occur after fully comprehending the current processes. Without a solid grasp of the existing facility operation, no improvements can be made. Once this understanding is achieved, lean principles can then be applied to modify the system. Lean theory serves as the primary catalyst for suggesting methods to minimize downtime and increase throughput. The Toyota Production System (Krijnen, 2007) outlines two key principles that were instrumental in developing alternative approaches to the facility operation:

- Principle 12: "Go and see for yourself to thoroughly understand the situation".

Production problems often have underlying root causes that can't be fully uncovered without direct observation. This principle encourages observing and understanding the actual processes and problems on the ground. This hands-on approach ensures informed decision-making based on real, firsthand insights. Rather than relying on assumptions based on opinions or reports, it's essential to verify the data firsthand by visiting the shop floor and identifying the true source of the issue. A superficial understanding of the problem can lead to suboptimal or even ineffective improvements.

- Principle 13: "Make decisions slowly by consensus, thoroughly considering all options; implement decisions rapidly".

This principle ensures well-informed decisions with broad support, leading to more effective execution. Principle 13 was consistently applied throughout the study, particularly during the time spent at the facility and during the development of the simulation model. This approach proved valuable in gathering insights from the operators, who, without realizing it, already practiced lean philosophy intuitively. Since production issues directly impact the operators, it is crucial to involve them in the process of improving the production system. Once the problem is understood and data is collected, options are presented for further investigation. Based on the analysis of the initial findings, an action plan is then developed to swiftly implement the agreed-upon decisions.

The proposed interventions impose a change in the operation and maintenance of the facility and require the acceptance of upper management and operators. The suggested interventions revolved around the idea of the reducing downtime of the facility. During the study discussions with operators and facility engineers were held about the issues and problems faced, as they are familiar with the repetitive nature of their tasks, they can propose practical improvements that would simplify their work. Some of the issues faced at the facility included, frequent breakdown of major machines, long repair times and wait times for parts. The proposed interventions are derived from those issues. One of the ideas is to propose a preventive maintenance system. Another idea is to implement a policy that would help with reducing the long repair times. Lastly, was the idea of operating both lines of the facility, in a way where one would be operating when the other is down.

The issues faced in the facility need to be discussed with the operators regularly, this should never be disregarded, as doing so can lead to a loss of momentum and leave operators feeling discouraged when their input is not valued. It's important to approach the process with the intention of implementing their suggestions and recognizing the knowledge of those who contribute. This strategy cultivates a work environment where everyone is motivated to participate and share ideas, driving innovation. Moreover, operators are more likely to anticipate work positively, knowing they are integral to the improvement process.

The key factor is consistency. For the cultural shift described above to take place, it must begin with a shift in the mindset of upper management. This process is challenging and requires time and patience, as such changes are gradual and don't happen instantly. With persistent effort and continuous encouragement for operators to engage in the improvement process, momentum will build, and eventually, the workflow will operate smoothly on its own. The real secret is initiating this change and staying committed until it becomes the standard practice.

This chapter touches on the potential solutions to the current operation of the waste facility, as well as on the behavior of the system when presented with the proposed interventions from a production perspective, obtained from the results of the simulation models developed.

7.2. Proposed interventions

Once the analysis and validation of the base model representing the real-world model, three interventions are proposed to implement improvements from a lean thinking perspective.

7.2.1. Intervention 1: Preventive Maintenance

The first intervention consists of implementing a preventive maintenance approach at the facility, where the maintenance crew will perform checkups on all the machines to assess their conditions, and perform any needed maintenance, furthermore it will also allow to identify an issue that has started to build up and can develop into severe problems in the system, causing prolonged downtimes. Hence this approach will reduce risk of major breakdown, as it allows to reduce the probability of breakdown by 30 to 50% (Yazdi, 2024). It is important to note that this checkup will be performed outside of the daily 10-hour operation time where the facility is expected to be running.

7.2.2. Intervention 2: Policy to Reduce Repair time

The second intervention consists of applying a policy that will achieve lower repair time, for example keeping inventory of the parts needed for repairs and maintenance at the facility, where the maintenance crew will have immediate access to these parts after the assessment of the situation and finding the source of the issue, allowing for faster repairs, hence the facility will be able to back to operation faster. Studies have shown this policy has helped facilities decrease breakdown time by 20 to 50 % (Muchiri et al., 2014).

7.2.3. Intervention 3: Operate on Both Lines

The Third proposed intervention consists of utilizing the design of the facility, was it has two parallel identical lines in parts of the system. When a breakdown happens, instead of shutting down the entire facility, only the segment where the breakdown is located seizes to receive MSW and the flow is diverted to the second line; this would happen in two scenarios:

1. A breakdown takes place in one of the parallel lines of the PPF, then the MSW will be sent fully to the other line (the production rate will not change).
2. A breakdown takes place in one of the parallel lines of the RDF, then the MSW will be sent to the other line (the production rate will not change), this line will remain the operating line until it suffers a breakdown takes place.

If the breakdown takes place in the part of the RDF where only one line exists, then the whole facility will shut down, as it happens in the base model.

This study has considered the scenario where one of line is undergoing maintenance, and its parallel line breaks down, then whole system will shut down.

7.3. Simulation of Interventions

7.3.1. Intervention 1: Preventive Maintenance

Figures 17,18 and 19 below show the simulation model developed to simulate the impact of preventive maintenance on the facility, which should yield a breakdown probability that is 40% lower than the base scenario. The simulation outputs the key metrics and compare them with the metrics collected from the base model.

The major difference in the simulation model from the base model is the probability of breakdown, a factor of 40% was adopted in this study to avoid optimistic and pessimistic extremes of the range found in literature mentioned before. It is important to note that when the runtime reaches 1000 hours, the probability of breakdown remains 1.00, as it allows to respect the assumption made at the beginning of the process, that the system will be shut down after 1000 hours of runtime to perform maintenance. Table 5 displays the difference in probability between the base model and the model with the preventive maintenance.

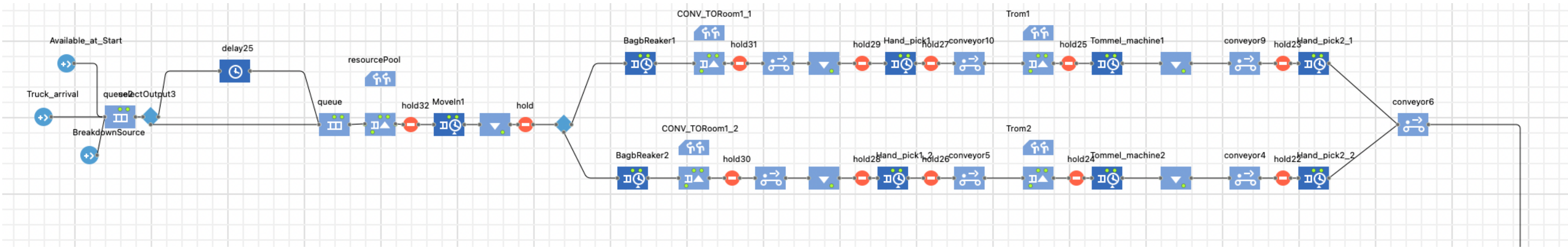

Figure 17: IPTF Simulation Model with Preventive Maintenance part 1

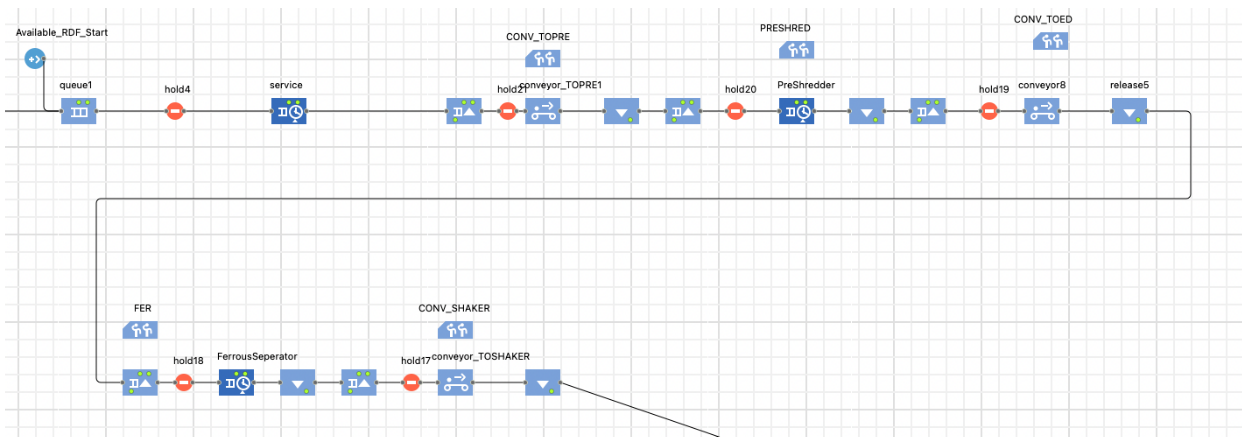

Figure 18: IPTF Simulation Model with Preventive Maintenance part 2

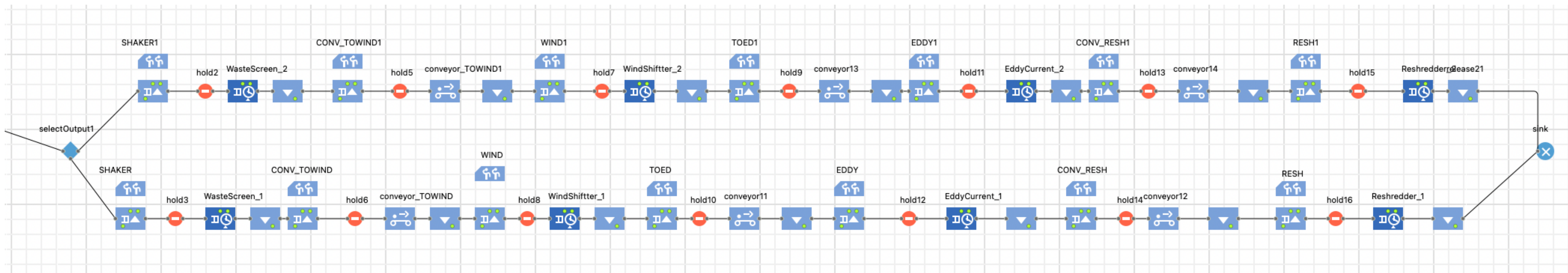

Figure 19: IPTF Simulation Model with Preventive Maintenance part 3

Table 5: Probability of breakdown Ranges of Base Model Vs. Intervention 1

Runtime Range in Hours	Probability of Breakdown Base Model	Probability of Breakdown Intervention 1
0 to 99	0.00	0.00
100 to 299	0.3125	0.1875
300 to 499	0.5313	0.3188
500 to 999	0.7188	0.4313
Over 1000	1.00	1.00

7.3.2. Intervention 2: Repair Time Reduction

Figures 20,21 and 22 below show the simulation model developed to simulate the impact of applying a policy that would decrease the repair times of the machines, such as keeping inventory of all needed parts for repairs, keeping parts that require the longest shipping time, or reducing procurement time of needed parts. Consequently, get the key metrics and compare them with the metrics collected from the base model.

The major difference in the simulation model from the base model is the Repair time, a factor of 30% was adopted in this study to avoid optimistic and pessimistic extremes of the range found in literature previously mentioned. Table 6 represents the repair time distributions for the new model with intervention 2, compared to Table 3 that represents these distributions for the base model.

Table 6: Repair time distribution of Intervention 2

Level	Distribution (in Hours)
Cleaning and Small Maintenance	Triangular (1.3, 6.5,3.25)
Repairs	Triangular (6.825,13,9.75)
Major Upgrades	Triangular(13.325,135.85,30.719)

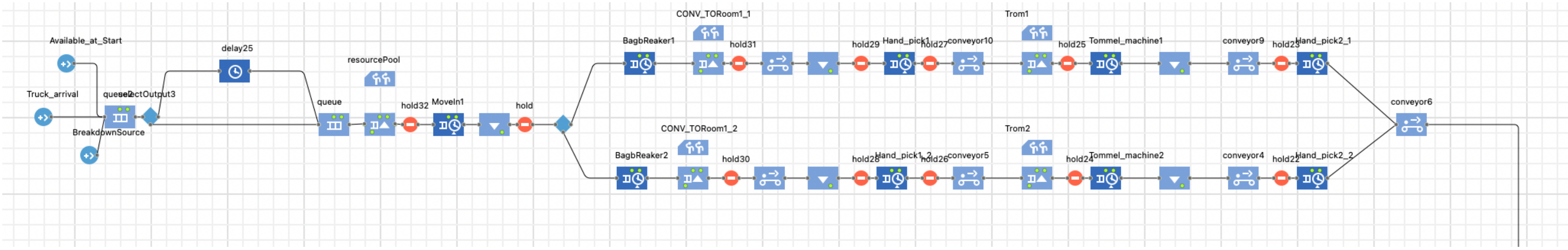

Figure 20: IPTF Simulation Model with Intervention 2 Part 1

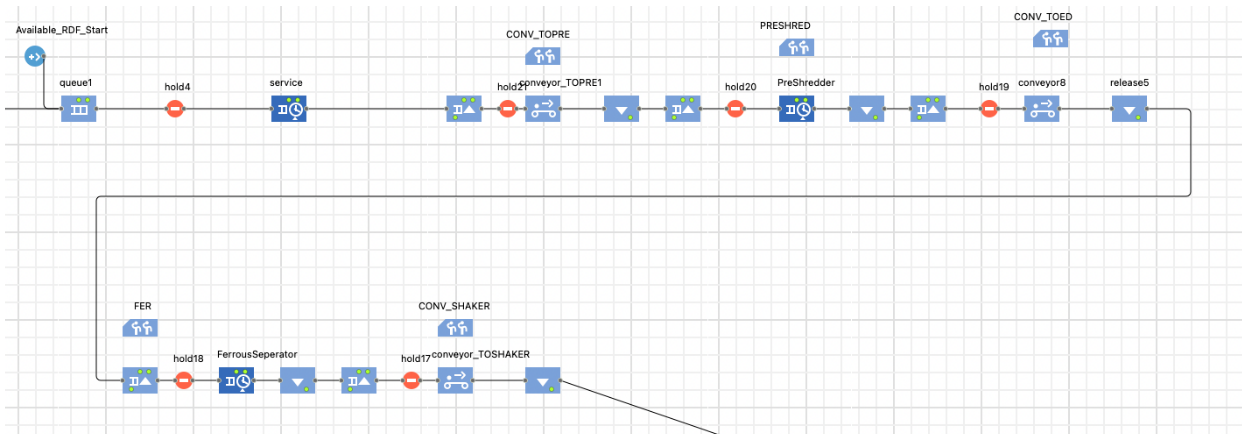

Figure 21: IPTF Simulation Model with Intervention 2 Part 2

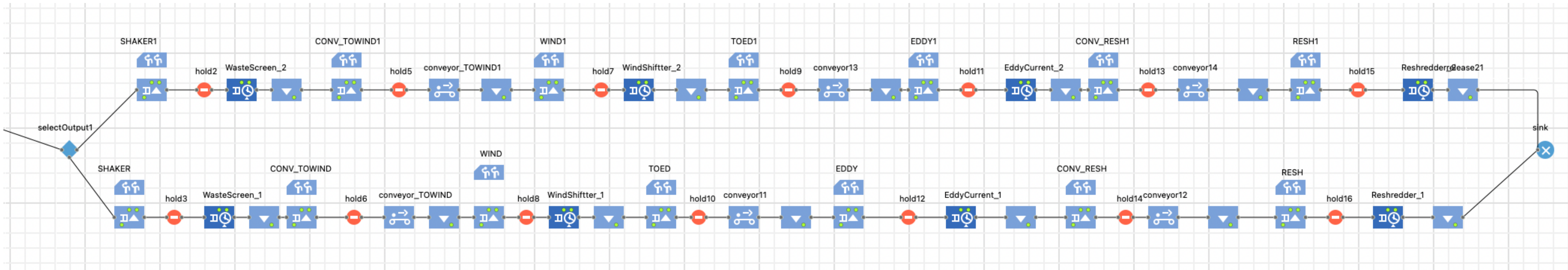

Figure 22: IPTF Simulation Model with Intervention 2 Part 3

7.3.3. Intervention 3: Operate on Both Lines

Figures 23, 24 and 25, below shows the simulation model developed to simulate the impact of Operating with both lines on the facility, and consequently get the key metrics and compare them with the metrics collected from the base model.

The major difference in the simulation model from the base model is the stop blocks present after every machine, as mentioned before they control the flow in the simulation model when a breakdown occurs. In this simulation model, instead of blocking all machines, it will only block the machines in the respective location. The location of the breakdown is simulated using a randomly generated number between 1 and 5, equally probable, which is generate every time the breakdown occurs.

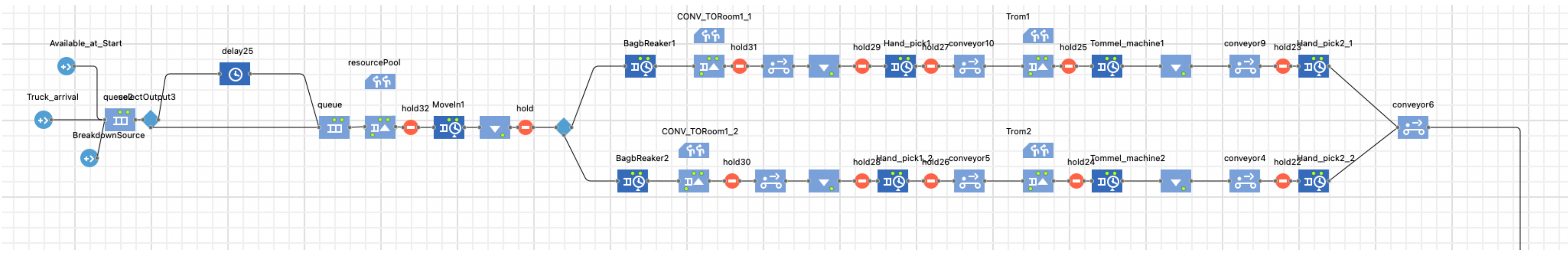

Figure 23: IPTF Simulation Model with Intervention 3 Part 1

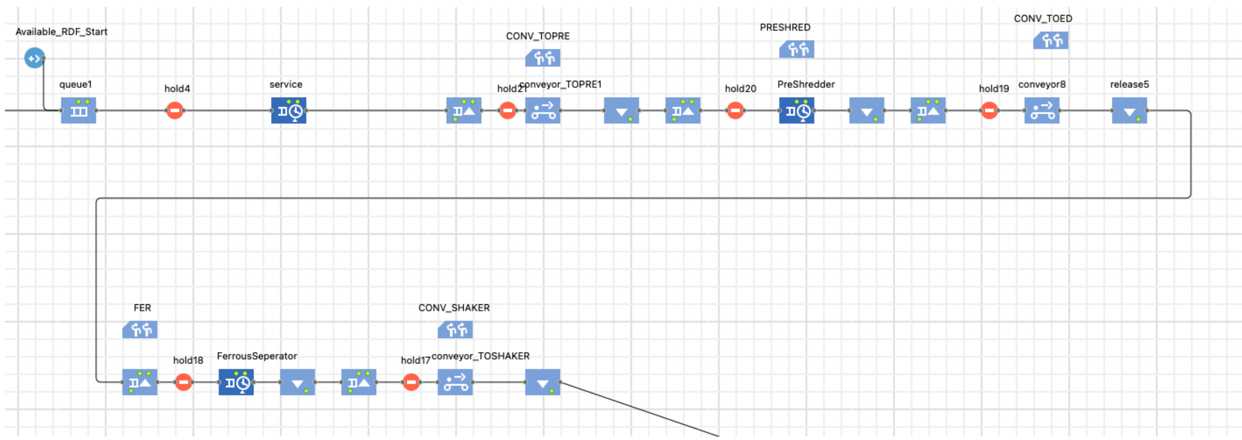

Figure 24: IPTF Simulation Model with Intervention 3 Part 2

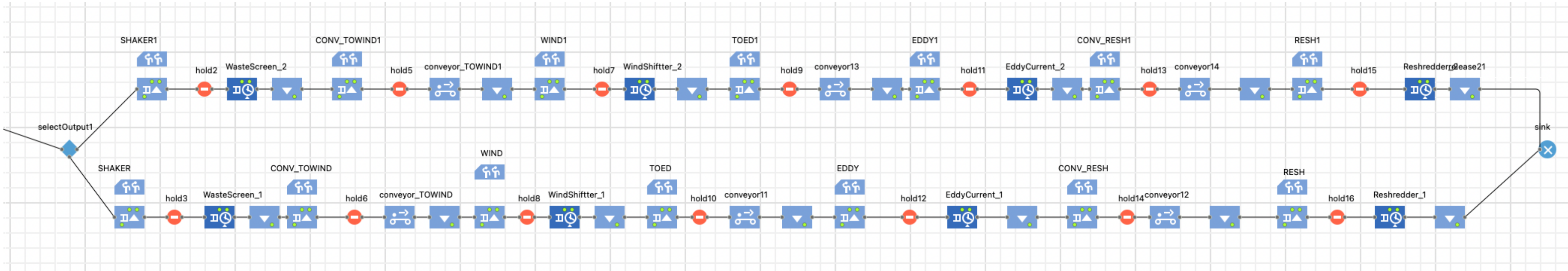

Figure 25: IPTF Simulation Model with Intervention 3 Part 3

7.3.4. Combination of Interventions

After simulating the base case scenario and three different interventions, it is crucial to compare them to determine the most optimal solution for improving the facility runtime. The analysis focused on the following metrics downtime %, total runtime, and total throughput. Additionally, the effects of combining the selected interventions were also simulated and analyzed. The chapter concludes by recommending the intervention or combination of interventions that would provide the best results.

The combinations of interventions are the following:

- Intervention 1+2: Consists of implementing preventive maintenance with a policy that reduces repair times.
- Intervention 1+3: Consists of implementing preventive maintenance, and running both lines of the system, only shutting down the part where the breakdown took place and diverting the flow to the second line.
- Intervention 2+3: Consists of adopting a policy that reduces repair times, and running both lines of the system, only shutting down the part where the breakdown took place and diverting the flow to the second line.
- Intervention 1+2+3: Consists of implementing preventive maintenance, while adopting a policy that reduces repair times, and running both lines of the system, only shutting down the part where the breakdown took place and diverting the flow to the second line.

7.3.4.1 Intervention 1+2

In this intervention, the simulation model developed to simulate the impact of preventive maintenance combined with a policy that reduces repair times, and consequently get the key metrics and compare them with the metrics collected from the base model.

The major differences in the simulation model from the base model is the probability of breakdown which is 40% lower, and a breakdown time that is 30% lower.

7.3.4.2. Intervention 1+3

In this intervention, the simulation model developed to simulate the impact of preventive maintenance combined with the diverting the flow of MSW to the parallel line when a breakdown happens, and consequently get the key metrics and compare them with the metrics collected from the base model.

The major differences in the simulation model from the base model is the probability of breakdown which is 40% lower, and stop blocks will not block all machines, it will only block the machines in the respective location where the breakdown happened and divert the flow to the parallel line when possible.

7.3.4.3 Intervention 2+3

In this intervention, the simulation model developed to simulate the impact of a policy that reduces repair times, combined with the diverting the flow of MSW to the parallel line when a breakdown happens, and consequently get the key metrics and compare them with the metrics collected from the base model.

The major differences in the simulation model from the base model is the breakdown time which is 30% lower, and stop blocks will not block all machines, it will only block the machines in the respective location where the breakdown happened and divert the flow to the parallel line when possible.

7.3.4.4 Intervention 1+2+3

This option combines all the proposed lean interventions are combined, where the probability of breakdown is 40% lower, the breakdown time which is 30% lower, and stop blocks will not block all machines, it will only block the machines in the respective location where the breakdown happened and divert the flow to the parallel line when possible.

7.4. Results and Discussion

As previously mentioned, the three metrics (Downtime %, Total Runtime and Total Throughput) used to assess the state of the system are collected from the simulation models, they are then compared to the base model, and amount each other to provide the best recommendations to improvement of the facility. The models were all ran over a period of 3600 hours.

It is important to mention that the results and analysis of these simulations are not aimed at making a decision, but rather help the facility managers make more informed decisions for changes in the operation or structure of the facility and set the basis for a return-on-investment study. As they will be able to visualize how an intervention will impact the facility, from the productivity point of view, and decide if the cost of this intervention is justified.

The Graphs for each of the three metrics, for the 150 runs of each intervention and their combinations can be found in Appendix B.

7.4.1. Downtime %

When simulating the three interventions proposed in this study, and their four combinations, a significate decrease in the Downtime % can be observed. This is directly related to the decrease in downtime in the 7 scenarios, compared to the base model.

Figure 26 below displays a box and whiskers graph of the downtimes obtained in the 50 runs for each scenario, paired with Table 7 which summaries the Downtime % of each scenario, allowing to visualize the effects of the interventions.

We can see that the base model has the highest downtime, sitting at 18.43%, with an average downtime of 663.48 hours. Interventions 1 and 2, have about the same impact on the system reducing the downtime to 11.87% and 10.63%, with average downtimes of 427.32 hours and 382.68 hours, respectively. Among the three improvements, Intervention 3 has had the biggest impact on the system reducing the downtime to 5.25 %with average downtimes of 188.85 hours, this impact was expected as the only time we have a downtime is when the line is switching due to a breakdown in one of the parallel lines, which is very brief moment, or when a breakdown takes place in the RDF single line, which forces the whole facility to shut down.

As for the combination of interventions, the scenario with the smallest impact on the system is the Intervention 1+2, reducing the downtime to 7.68 %, with average downtimes of 276.48 hours. Followed by Intervention 2+3, reducing the downtime to 3.58 %, with average downtimes of 129.03 hours. interventions 1+3 and 1+2+3, have about the same impact on the system reducing the downtime to 2.51 % and 2.40 %, with average downtimes of 90.36 hours and 86.40 hours, respectively.

A benefit of the box and whiskers graph is the ability to compare more than the average value of the different scenarios, it provides a wider understanding of the behavior of the scenarios. Most notably the variability of the output in each scenario.

Looking at Figure 26, the base model has the highest variability of all the scenarios. Comparing the three interventions, Scenario 1 leads the way with the highest variability, where scenarios 2 and 3 have about the same variability.

As for the combinations, Scenario 1+2 leads with the highest variability, but is still lower than Scenario1. Scenarios 1+3 and 2+3 have about the same variability, very similar to that pf scenarios 2 and 3, while Scenario 1+2+3 displayed the lowest variability.

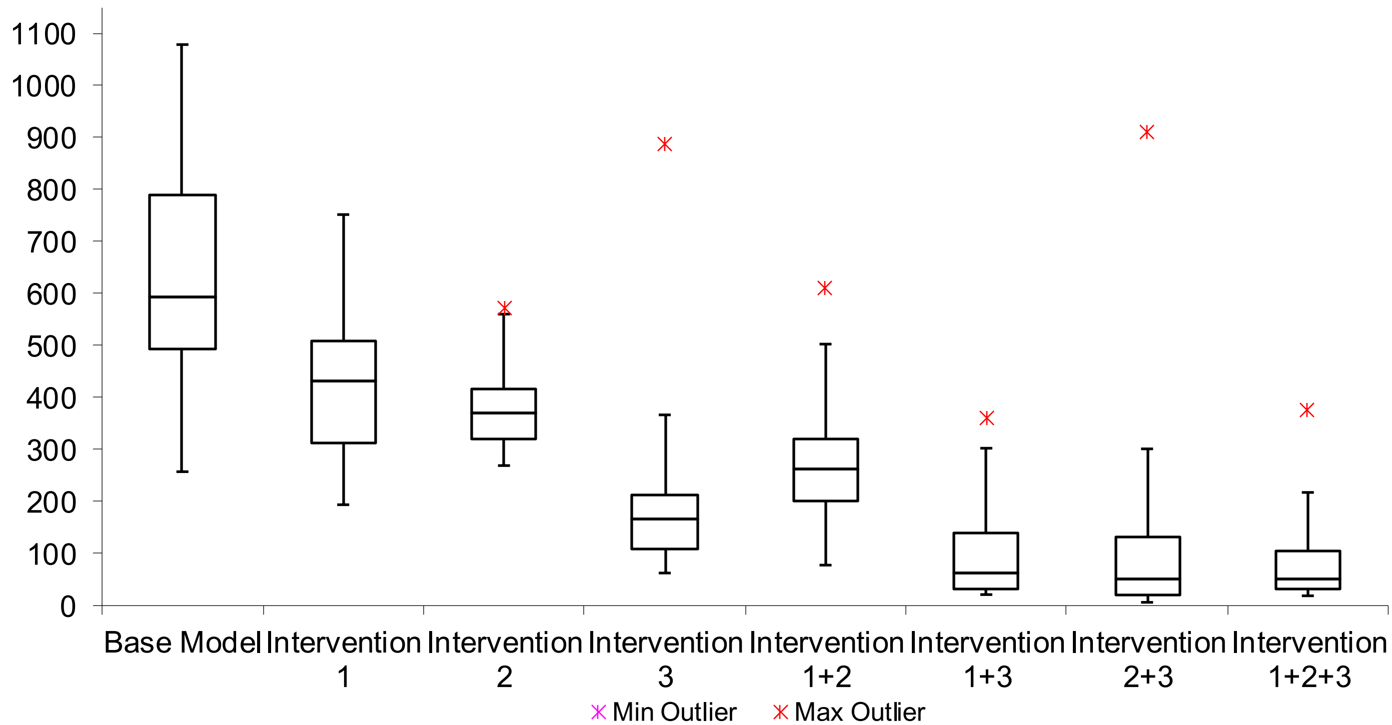

Figure 26: Box and Whiskers Graph for Downtime of the Models

Table 7: Downtime Percentage of Each Model

Model	Downtime %
Base Model	18.43%
Scenario 1	11.87%
Scenario 2	10.63%
Scenario 3	5.25%
Scenario 1+2	7.68%
Scenario 1+3	2.51%
Scenario 2+3	3.58%
Scenario 1+2+3	2.40%

7.4.2. Total Runtime

The total Runtime of the three interventions proposed in this study, and their four combinations, being collected from the from the simulation models, it is calculated as all-time outside of breakdowns. Comparing the different interventions with the base model, we can see that the interventions have allowed for an increase in runtime.

Figure 27 below displays a box and whiskers graph of the Runtime obtained in the 50 runs for each scenario, paired with Table 8 which summaries the Runtime of each scenario, allowing to visualize the effects of the interventions.

Here the base model has the lowest runtime, sitting at an average of 2936.52 hours. Where among the three interventions, preventive maintenance (intervention 1) has the lowest runtime at 3172.68 hours, followed by intervention 2 at 3217.32 hours, and the biggest improvement is intervention 3 where the runtime increases to 3411.145 hours.

As for the combination of interventions, the scenario with the smallest impact on the system is the Intervention 1+2, increasing runtime to 3323.52 hours. Followed by Intervention 2+3, increasing runtime to 3470.97 hours. interventions 1+3 and 1+2+3, have about the same impact on the system increasing runtime to 3509.64 hours and 3513.60 hours, respectively.

As for the variability, Figure 27 shows how the base model has again the highest variability of all the scenarios. As for the three interventions, Scenario 1 has the highest variability, while scenarios 2 and 3 have about the same variability.

Looking at the combinations now, Scenario 1+2 leads with the highest variability, as for Scenarios 1+3 and 2+3 they have about the same variability, very similar to that pf scenarios 2 and 3, while Scenario 1+2+3 displayed the lowest variability.

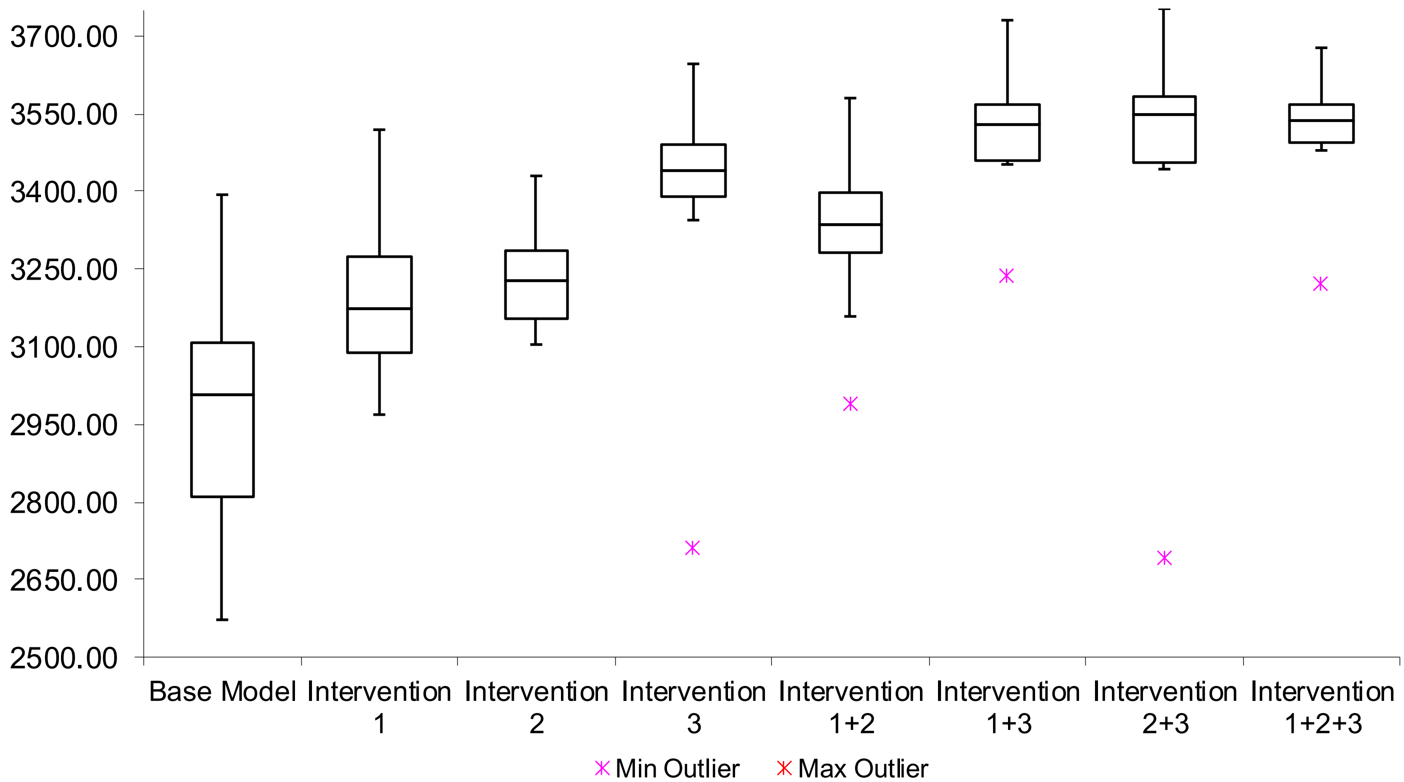

Figure 27: Box and Whiskers Graph for Runtime of the Models

Table 8: Total Runtime of each Model (in Hours)

Model	Total Runtime in Hours
Base Model	2936.52
Scenario 1	3172.68
Scenario 2	3217.32
Scenario 3	3411.15
Scenario 1+2	3323.52
Scenario 1+3	3509.64
Scenario 2+3	3470.97
Scenario 1+2+3	3513.60

7.4.3. Throughput

The total generate tonnage of the three interventions proposed in this study, and their four combinations, was collected from the from the simulation models. Comparing the different interventions with the base model, we can see that the interventions have allowed for an increase in throughput.

Figure 28 below displays a box and whiskers graph of the Throughput obtained in the 50 runs for each scenario, paired with Table 9 which summaries the Throughput of each scenario, allowing to visualize the effects of the interventions.

Here again the base model has the lowest throughput, sitting at an average of 26666.94 tons. Among the three interventions, intervention 1 ranks the lowest at 29384.12 tons produced, followed by intervention 2 at 29946.91 tons, and the biggest improvement is intervention 3 where the throughput increases to 32367.55 tons.

As for the combination of interventions, the scenario with the smallest impact on the system is the Intervention 1+2, increasing throughput to 31149.58 tons. Followed by Intervention 2+3, increasing to 32099.38 tons. Intervention 1+3 and Intervention 1+2+3, have about the same impact on the system increasing throughput to 32557.91 tons and 32679.70 tons, respectively.

Looking at the variability, using Figure 28 we can see that the base model has again the highest variability of all the scenarios. As for the three interventions, Scenario 1 again has the highest variability, while scenarios 2 and 3 have about the same variability.

Looking at the combinations now, Scenario 1+2 leads with the highest variability, followed by Scenario 2+3, and finally scenarios 1+3 and 1+2+3 have about the same variability, being the lowest we see among the scenarios.

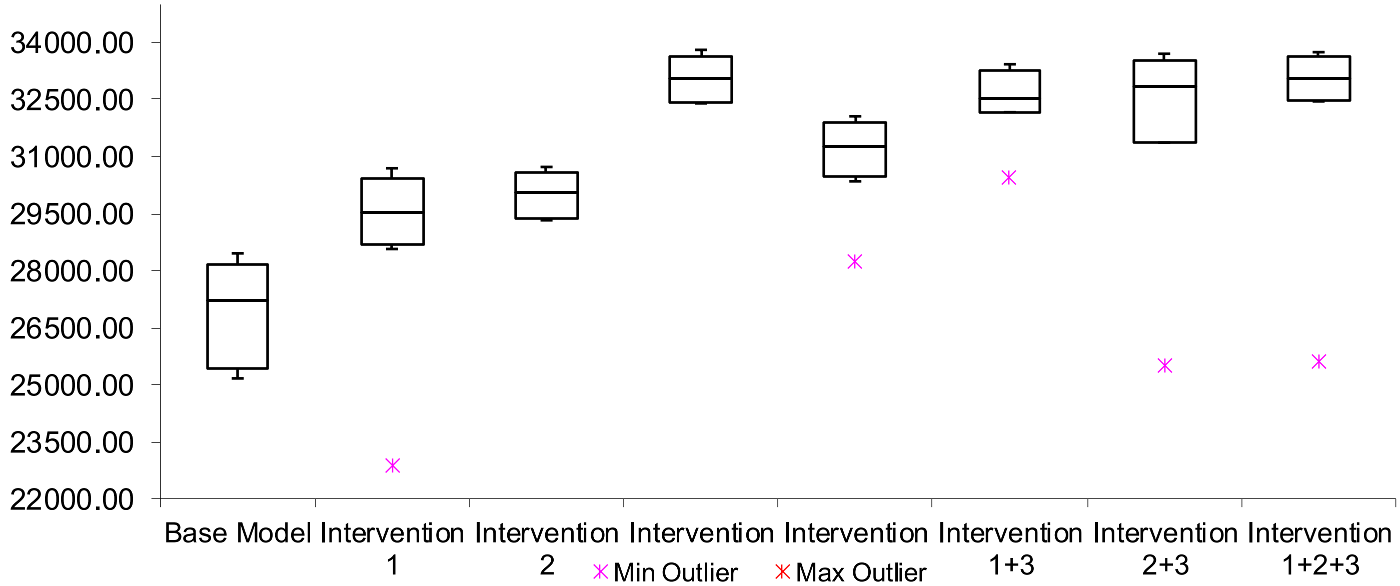

Figure 28: Box and Whiskers Graph for Throughput of the Models

Table 9: Total Throughput of each Model

Model	Total Throughput in Tons
Base Model	26666.94
Scenario 1	29384.12
Scenario 2	29946.91
Scenario 3	32367.55
Scenario 1+2	31149.58
Scenario 1+3	32557.91
Scenario 2+3	32099.38
Scenario 1+2+3	32679.70

7.5. Implication of results

The results discussed and compared above, provide a better understand of the impact of the different interventions and their respective interventions on the facility's operation and performance, it does not give us a clear answer on the best approach to take. Looking solely at metrics considered in this study, it would make the most sense to adopt the combination of all three of the interventions (intervention 1+2+3), implementing preventive maintenance which should yield a breakdown probability that is 40% lower than the base scenario, combined with the policy that would decrease the repair times of the machines by 30%, in addition to diverting the flow of MSW to the parallel line when a breakdown happens, as this combination of interventions yielded the the lowest downtime %, the highest runtime and the highest throughput, as well as the lowest variability in the results.

Yet the facility manager might walk away from this intervention, as it might be the costliest, or the return on investment to implement this approach might not be worth it for them.

It is important to note that these results are obtained using the metrics considered in this study, a study considering another set of factors and assumptions might result in different findings.

7.6. Conclusion

This chapter discussed the different lean interventions and their combinations, after analyzing the current state of the production system. The different solutions proposed in this study come from the time spent at the facility, the meetings with field experts and data collected. The proposed interventions were simulated individually, then in combinations of each other to study their impact on the production of the facility. Intervention 1+2+3 yielded the lowest downtime %, the highest runtime and the highest throughput, intervention 1+3 came very close to the results of intervention 1+2+3. As mentioned before, the decision on the best intervention for the facility can be justified by the cost of each intervention, hence it remains in the hands of the facility managers to make the decision that best fits the situation of the facility. It's important to acknowledge that several assumptions were made in this comparison. For instance, when addressing interventions 1 and 2, the study utilized the median value from the range provided in the literature. Additionally, there are various other factors that could be considered when comparing the three interventions and their respective combinations. The outcomes presented in this chapter are based on the developed simulation models, with the comparison primarily focused on downtime percentage and throughput. If different factors were analyzed, the results might differ.

Chapter 8 – Conclusion

8.1. Thesis Summary

The research presented in this thesis is firmly anchored in lean thinking and theory, applied specifically to the operations of a solid waste processing facility. This study employed a variety of lean tools and techniques, including Value Stream Mapping (VSM) and Simulation Modeling, to analyze and enhance the waste management process at the Solid Waste Management Facility (SWMF). The primary goal was to improve operational efficiency by reducing downtime, minimizing repair times, and increasing throughput, ultimately contributing to more sustainable and effective waste management practices.

The thesis began by highlighting the significant challenges faced in waste management, particularly the growing volume of municipal solid waste and the inefficiencies within processing facilities. It introduced the concept of lean thinking as a solution, drawing parallels to its successful application in manufacturing sector. Two central research objectives guided the study:

- Replicate the real-world solid waste processing facility through a simulation model that can be used to investigate different scenarios, and
- Develop and validate a set of lean interventions that are aimed to reduce downtime, and repair time to increase the production output.

The methodology adopted in this thesis is Design Science Research (DSR), comprising several critical steps: (1) Problem Identification, (2) Solution Development, and (3) Solution Evaluation. The core issue addressed in this research is the inefficiency in the solid waste processing at the Solid Waste Management Facility (SWMF), characterized by significant downtime, lengthy repair times, and suboptimal throughput. The study identifies the need to examine the waste processing flow from a lean perspective to reduce variability and enhance operational efficiency.

The artifact of this DSR methodology is a comprehensive simulation model framework, designed to analyze, evaluate, and improve the facility's operations. This framework is grounded in lean principles, focusing on waste reduction and process optimization. The framework was tested through a case study of the SWMF, where data collection and Value Stream Mapping were used to establish a baseline understanding of current operations.

The study is conducted in two phases. The first phase involves creating a base-case simulation model representing the facility's existing conditions. Chapter 5 introduces the development and validation of the Value Stream Map, while Chapter 6 details the construction of the simulation model based on this map. This model was crucial in obtaining metrics such as downtime percentage, total runtime, and throughput.

In the second phase, various lean interventions were proposed and simulated, each aimed at reducing downtime and enhancing production. Chapter 7 discusses these interventions, including (1) Preventive Maintenance, (2) Implementing a Policy to Reduce Repair Time, and (3) Operating both processing lines concurrently when breakdowns occur. The simulation results indicated that a combination of all three interventions (Intervention 1+2+3) yielded the most significant improvement, leading to the lowest downtime percentage, increased total runtime, and enhanced throughput, demonstrating a substantial improvement in the facility's operational efficiency.

8.2. Thesis Conclusion

The results obtained from the simulation models developed for improving the operations at the Solid Waste Management Facility (SWMF) yielded conclusive insights into the facility's performance and the impact of various lean interventions. The metrics collected, combined with observations on the current state of the facility, successfully provided a clear perspective on how waste processing operations can be optimized. This perspective directly addresses the research objectives set out at the beginning of this study:

1. Replicate the real-world solid waste processing facility through a simulation model: The state of the SWMF facility was meticulously analyzed to understand the flow of waste processing. This foundational step was crucial, as lean thinking is based on identifying problems at their root cause and ensuring that proposed solutions effectively target these issues. By accurately replicating the facility's operations in a simulation model, the study was able to pinpoint inefficiencies and test interventions in a controlled environment.

2. Develop and validate a set of lean interventions aimed at reducing downtime and repair time to increase production output: The study identified that multiple factors, such as equipment downtime and repair times, significantly impacted overall productivity. Several lean interventions were tested, including preventive maintenance, adopting a policy to reduce repair time, and optimizing the use of parallel processing lines. The findings demonstrated that while no single intervention could address all inefficiencies, a combination of strategies yielded the most substantial improvements in operational efficiency.

The tools and principles employed in this study were selected for their robustness and alignment with lean thinking. Value Stream Mapping was used to understand the current state of waste processing at SWMF. Simulation modeling allowed for the quantification and evaluation of these bottlenecks, providing metrics such as downtime percentage, total runtime, and throughput. The integration of these tools within a lean framework facilitated the effective improvement of the facility's operations.

In conclusion, the significance of direct observation and frequent site visits cannot be overstated. Engaging with on-site personnel and observing operations firsthand provided invaluable insights that were critical to understanding the flow of waste processing and the potential disruptions. This hands-on approach ensured that the interventions were grounded in the real-world challenges faced by the facility operators, leading to more practical and effective solutions.

8.3. Study Contribution

8.3.1. Academic Contributions

This thesis makes significant academic contributions by developing a framework aimed at understanding and improving operations at waste management facilities through the application of Value Stream Mapping and Simulation Modeling. The framework was designed using Design Science Research methodology and was validated through a case study of the Solid Waste Management Facility (SWMF). The study introduces lean practices to enhance efficiency, reduce downtime, and optimize waste processing. The interventions tested in this research demonstrate that applying lean tools in the context of waste management can substantially improve the productivity and reliability of such facilities. By simulating different scenarios and evaluating the outcomes, this research provides a structured approach for identifying and addressing inefficiencies in waste processing systems.

8.3.2. Industry Contributions

The study directly contributes to the waste management industry by offering practical solutions for improving facility operations. The interventions proposed in this research aim to minimize downtime, reduce repair times, and enhance overall throughput, leading to significant cost savings and better resource utilization. By implementing the lean interventions studied, waste management facilities like SWMF can achieve higher operational efficiency, reducing the environmental impact and operational costs associated with waste processing. The research also highlights the importance of preventive maintenance and strategic policy changes, such as inventory management, to streamline repair processes and ensure continuous operation. The framework and findings from this study can serve as a decision-aid tool for industry practitioners, guiding them in the implementation of lean practices to enhance their facility's performance. Furthermore, the approach of this study can be adopted and transferred to other facilities but not the data utilized.

In conclusion, the contributions of this study are multifaceted. First, it provides a detailed analysis of the current state of waste processing at the SWMF, identifying key areas for improvement. Second, it introduces a robust framework for applying lean principles to waste management, supported by simulation modeling. Third, the study validates the effectiveness of lean interventions in reducing downtime and increasing productivity, offering practical recommendations for industry application. Finally, the research underscores the importance of a holistic approach to facility management, where multiple interventions are combined to achieve optimal results.

8.4. Study Limitations

The study performed in this thesis includes several limitations. First, the Value Stream Map (VSM) developed does not account for the supply chain issues that may significantly impact the waste management process. Although the VSM has been validated by industry experts at the Solid Waste Management Facility (SWMF), incorporating supply chain dynamics could provide a more comprehensive understanding of potential disruptions and inefficiencies in the system. Second, the simulation model focuses solely on the base case scenario for the SWMF and does not consider the variability in waste composition or the impact of external factors, such as seasonal changes in waste generation. This limitation restricts the generalizability of the findings to other waste management facilities with different operational conditions. The data is limited on breakdown times and frequencies of individual machines to find their respective distributions; to find a distribution that can be modeled and avoid the use of deterministic values, a breakdown of the entire facility was adopted. Finally, the metrics used to assess the effectiveness of the interventions were limited to the specific conditions modeled in this study, and the findings may not directly translate to other facilities with different layouts, technologies, or operational strategies.

8.5. Future Research Recommendations

The research conducted in this thesis opens several avenues for future exploration, particularly in the context of improving municipal solid waste management at facilities like the SWMF. One key area for future research could involve extending the simulation models to incorporate the variability in waste composition and external factors, such as seasonal changes and supply chain disruptions. By doing so, a more robust and comprehensive framework could be developed to better reflect real-world conditions and improve decision-making processes.

Additionally, future studies could investigate the application of lean interventions to other waste processing systems beyond those examined in this thesis, allowing for a broader understanding of their effectiveness across different operational contexts. Incorporating additional metrics, such as resource usage by volume or weight, could also enhance the analysis and provide more granular insights into the impact of lean practices.

Moreover, integrating advanced technologies like computer vision for data collection and analysis could improve the accuracy and reliability of the simulation models, offering a more detailed view of facility operations. This approach would allow for real-time monitoring and more precise identification of inefficiencies.

Further research could also explore the intersection of waste management and design, particularly how early-stage design decisions influence the efficiency of waste processing systems. Investigating Lean Construction 4.0 and its potential application in waste management facilities could yield innovative solutions for reducing waste and variability, increasing value, and addressing broader legal and social implications. Ultimately, these future research directions aim to contribute to the development of sustainable, technologically advanced solutions for better managing waste processing facilities.

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Appendix A: Standard Error

The standard error (SE) is calculated by dividing the standard deviation (σ) of a sample by the square root of the sample size (n). The formula is:

$$\mathrm{SE} = \frac{\sigma}{\sqrt{\mathrm{n}}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \mathit{Equation}\ 4$$

This calculation gives an estimate of how much the sample mean is expected to vary from the true population mean, with a smaller SE indicating more precision in the estimate. One common rule of thumb is that the SE should be less than 10% of the mean. Through trial and error, the models were run until all SE were below the 10% mark. Table 10 below displays the calculations:

Table 10: Standard Error Calculation

Intervention	Standard Error		
	Throughput	Downtime	Runtime
Base Model	0.55%	2.35%	0.53%
1	0.42%	2.70%	0.36%
2	0.24%	1.99%	0.24%
3	0.51%	5.73%	0.32%
4	0.25%	2.96%	0.25%
5	0.22%	6.71%	0.17%
6	0.51%	9.23%	0.46%
7	0.40%	7.64%	0.19%

When we run each model 150 time, the Standard Error falls in the acceptable range, below the 10% mark.

Appendix B: Results of the interventions

B-1: Downtime of the models

The Figures below represent the Total Downtime for the 150 runs conducted for the models over a period of 3600 hours.

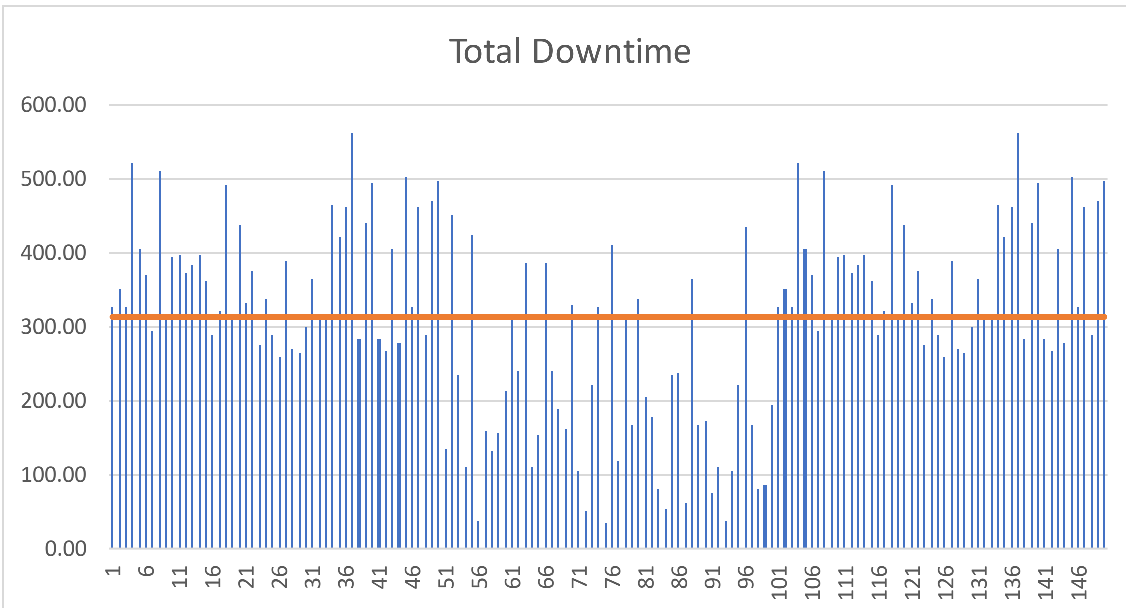

Figure 29: Downtime of Intervention 1

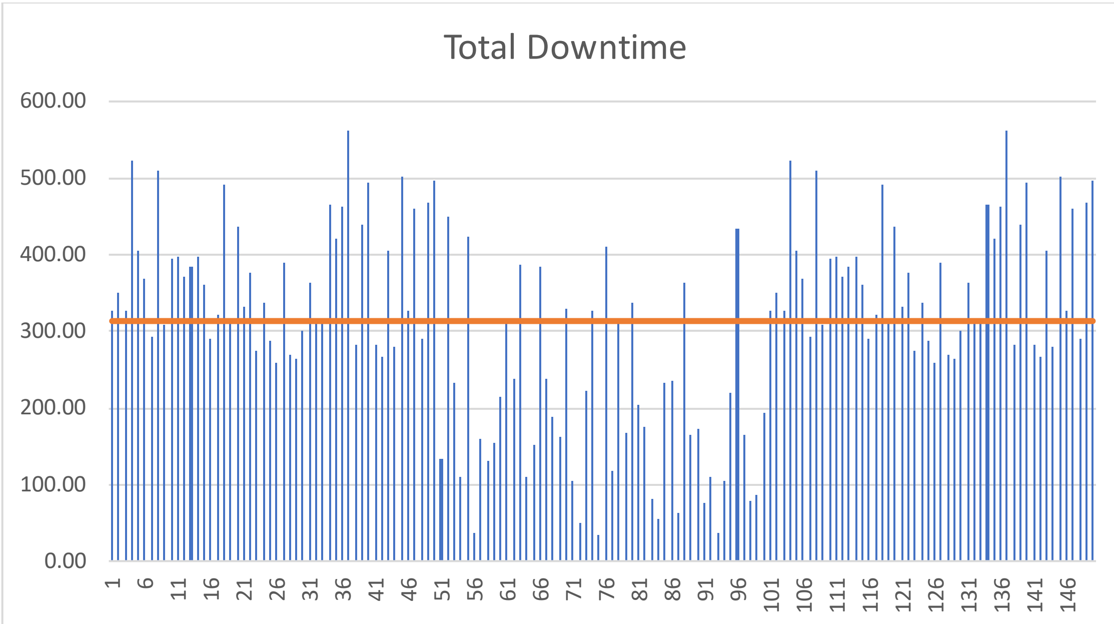

Figure 30: Downtime of Intervention 2

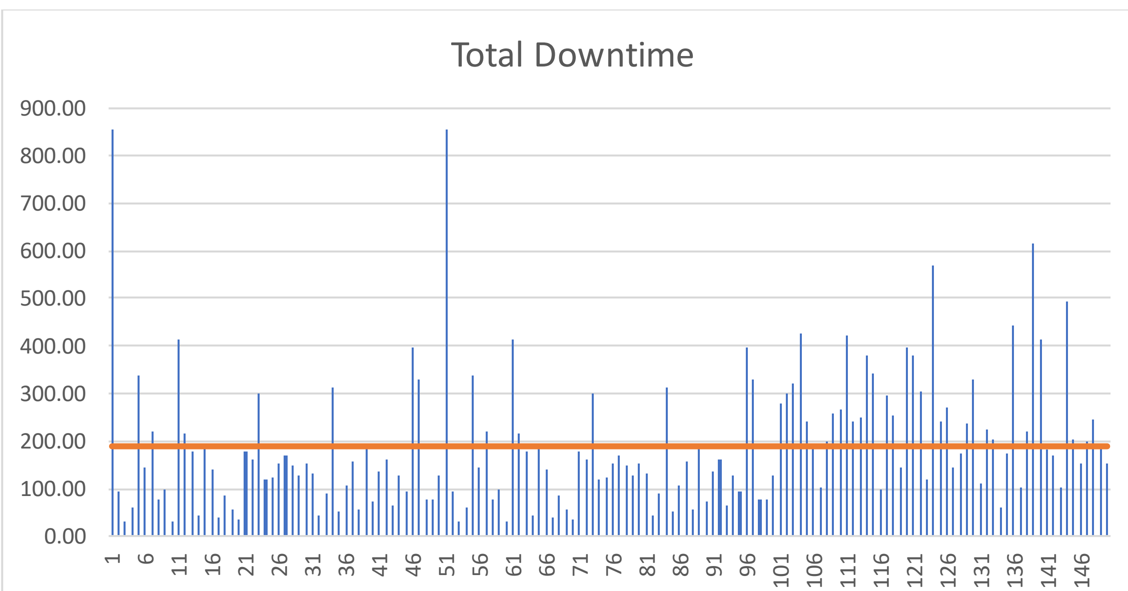

Figure 31: Downtime of Intervention 3

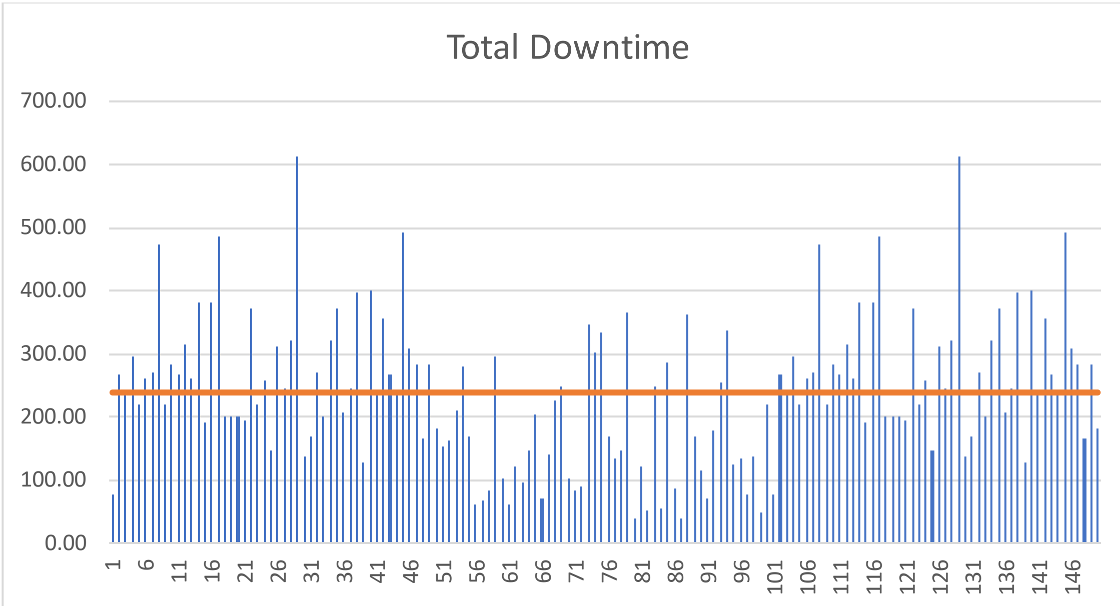

Figure 32: Downtime of Intervention 1+2

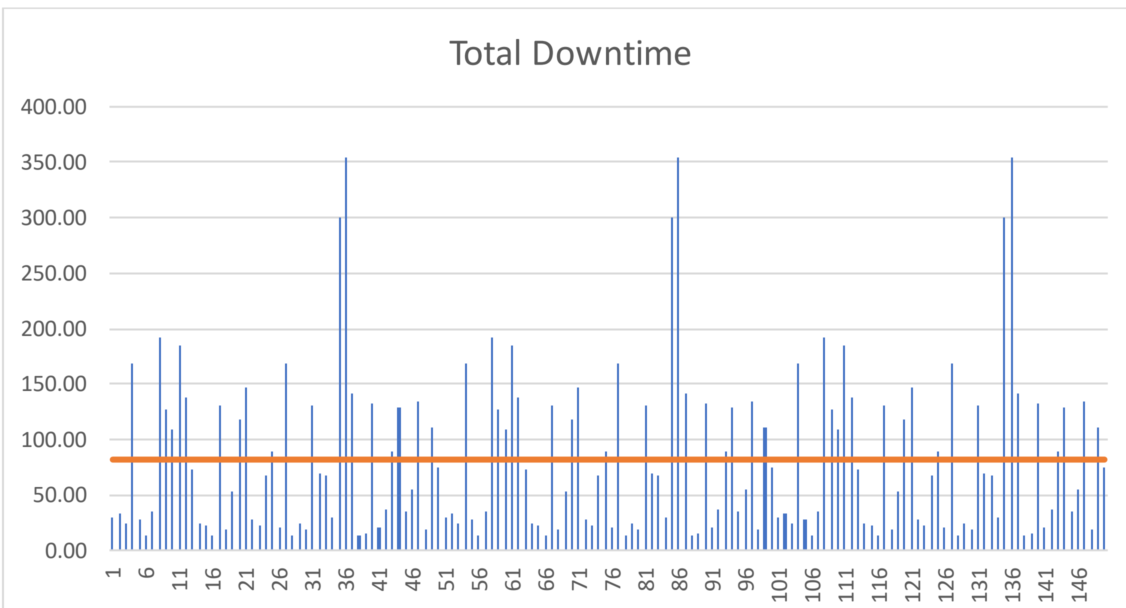

Figure 33: Downtime of Intervention 1+3

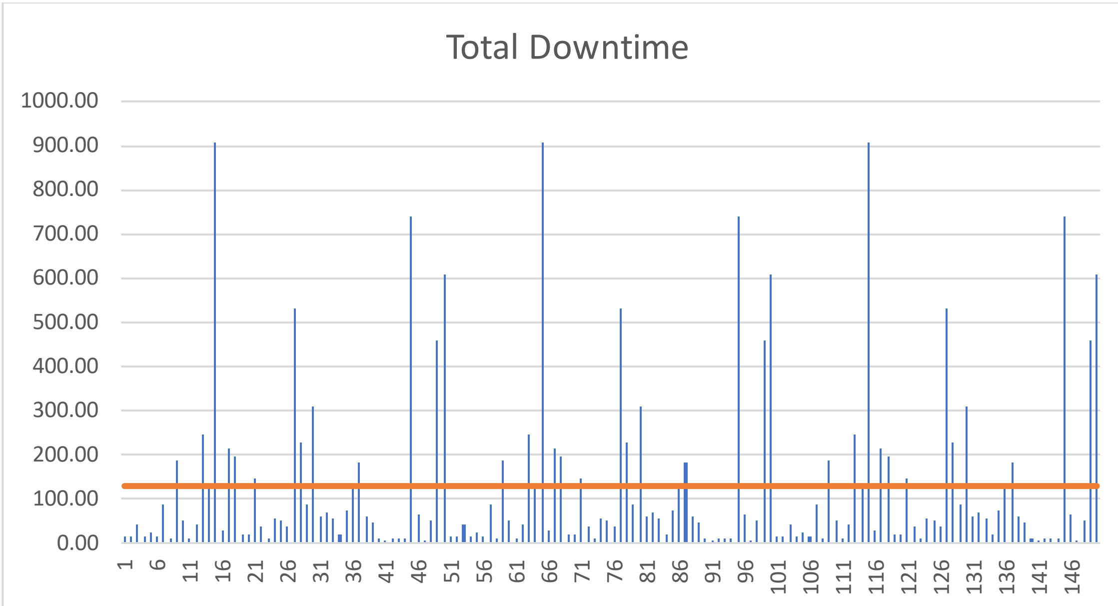

Figure 34: Downtime of Intervention 2+3

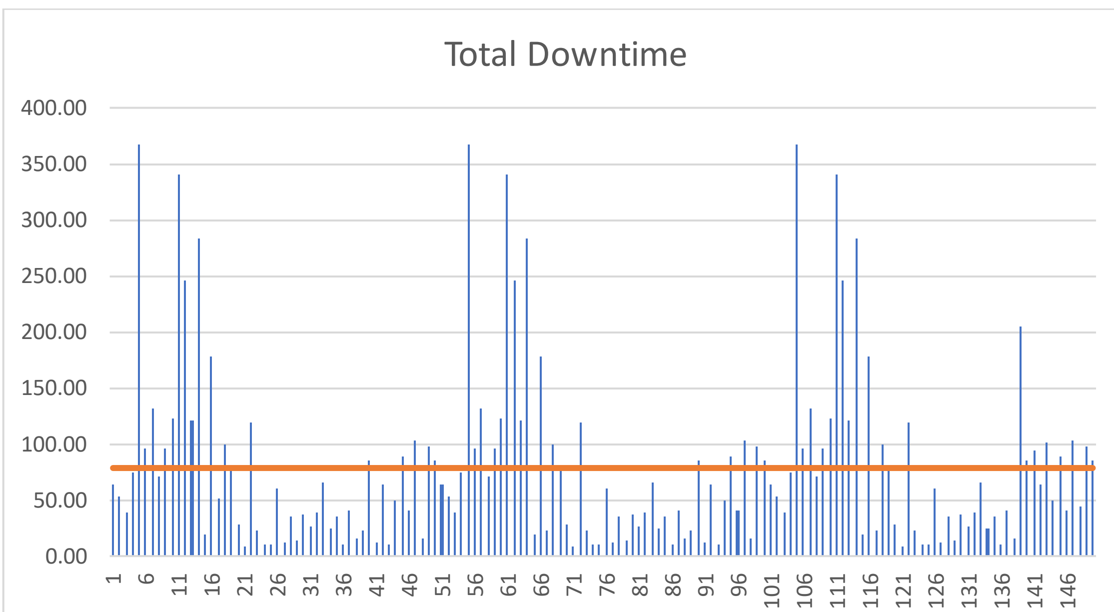

Figure 35: Downtime of Intervention 1+2+3

B-2: Runtime of the models

The Figures below represent the Total Runtime for the 150 runs conducted for the models over a period of 3600 hours.

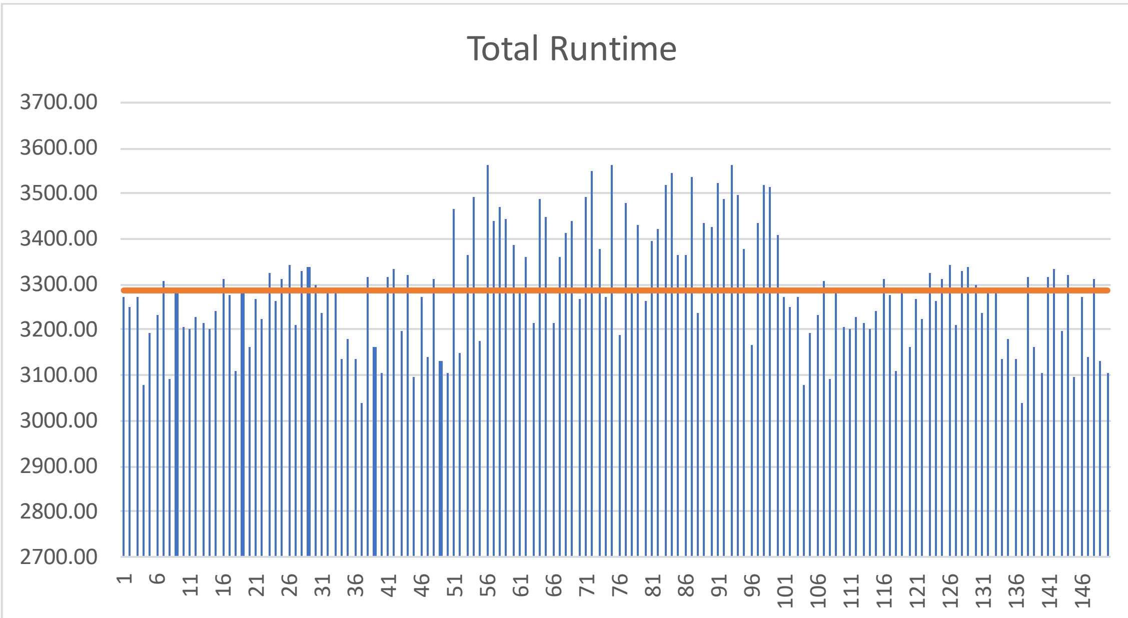

Figure 36: Runtime of Intervention 1

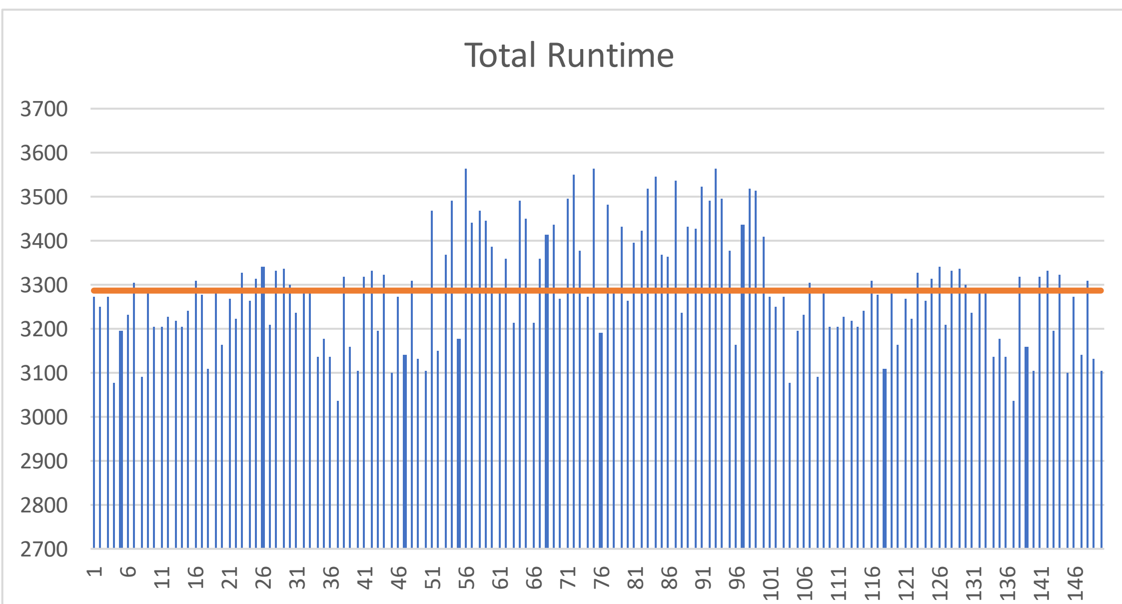

Figure 37: Runtime of Intervention 2

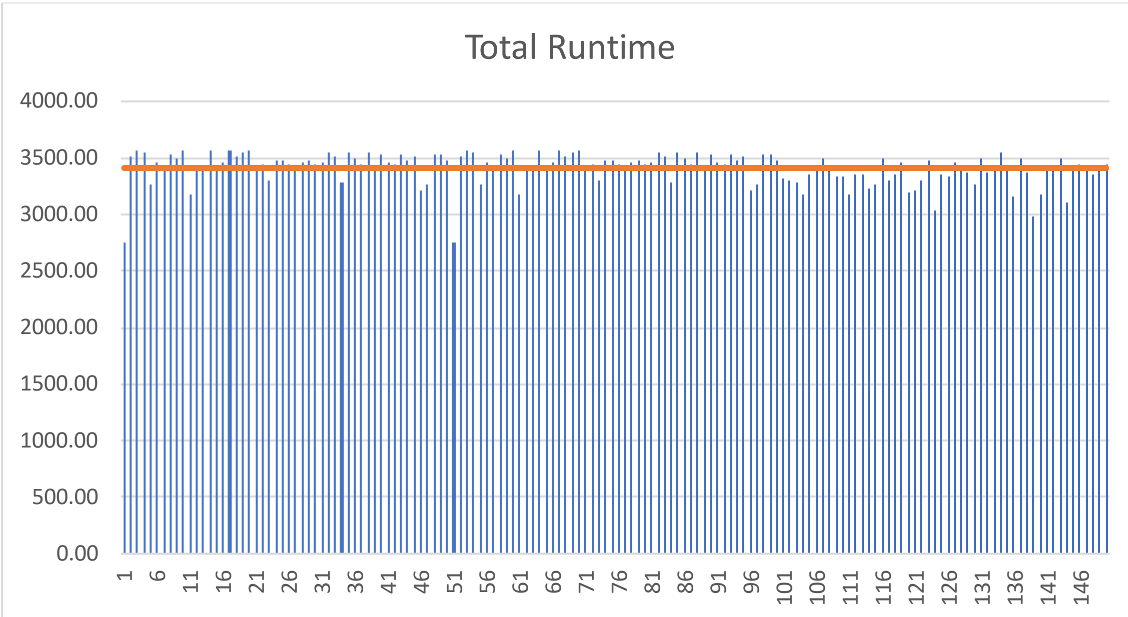

Figure 38: Runtime of Intervention 3

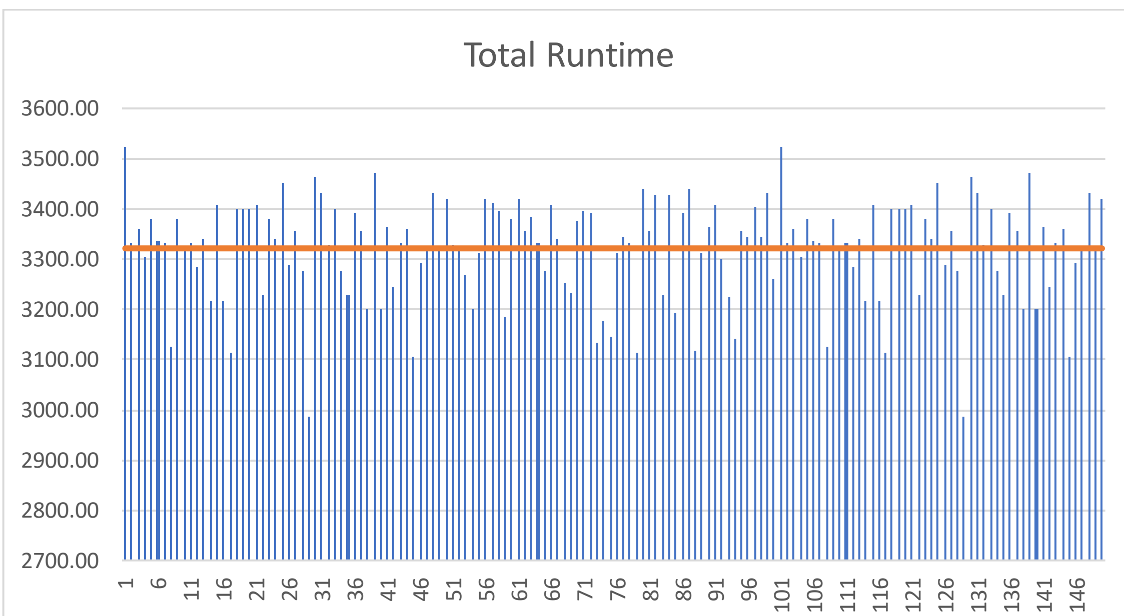

Figure 39: Runtime of Intervention 1+2

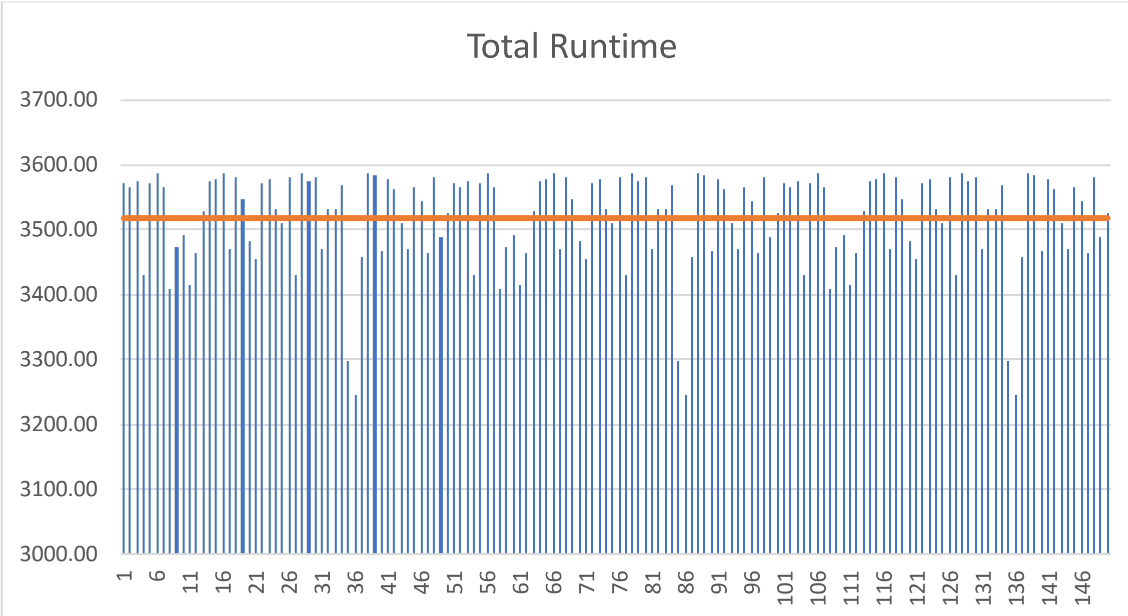

Figure 40: Runtime of Intervention 1+3

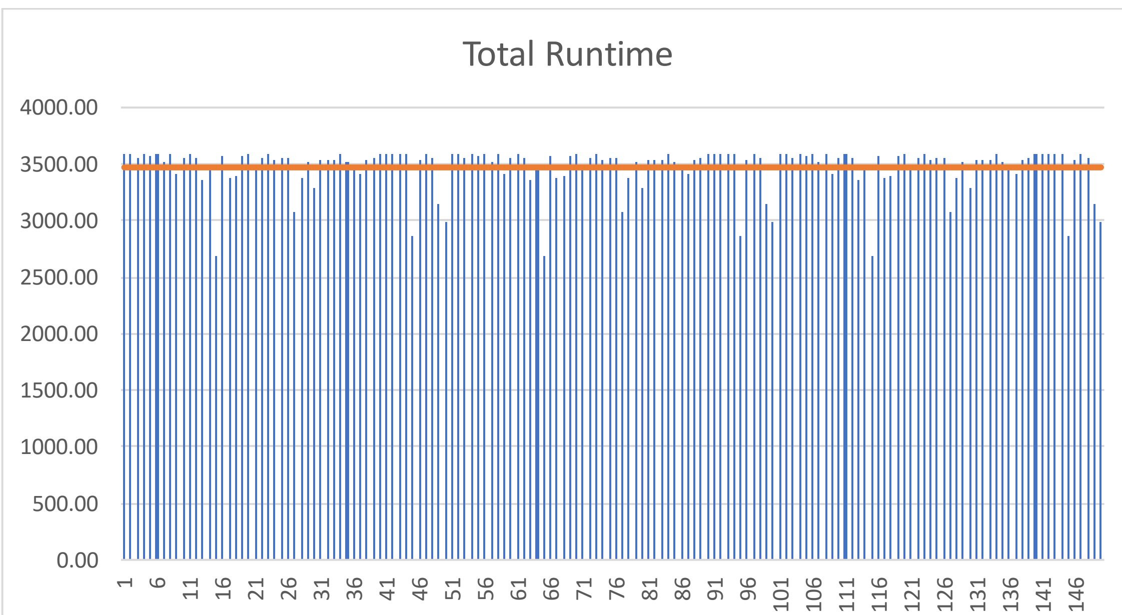

Figure 41: Runtime of Intervention 2+3

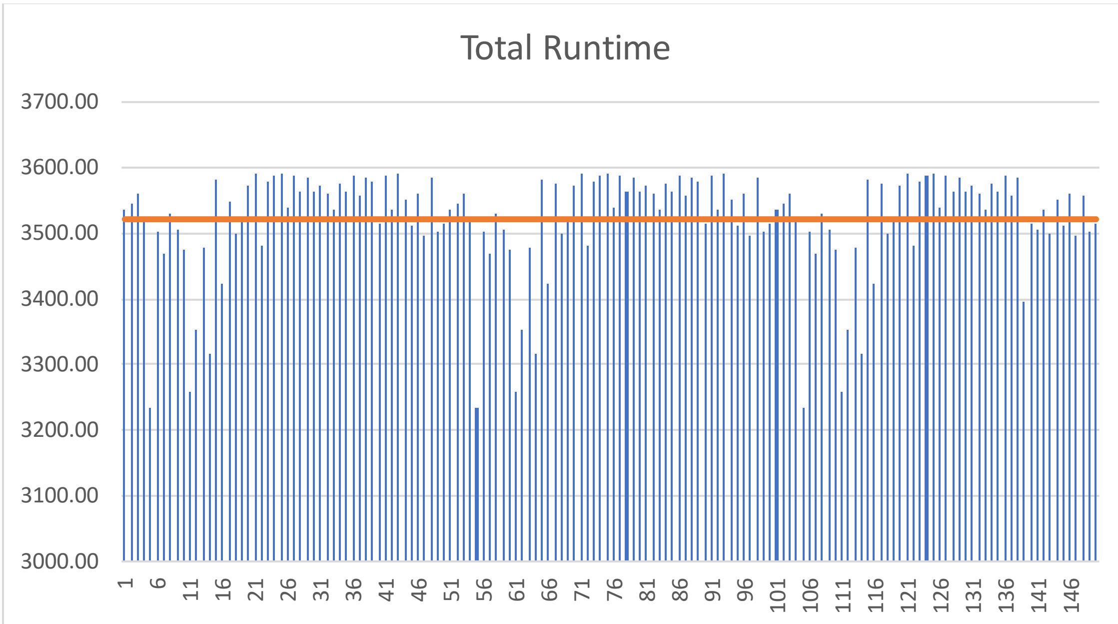

Figure 42: Runtime of Intervention 1+2+3

B-3: Throughput of the models

The Figures below represent the Total Throughput for the 150 runs conducted for the models over a period of 3600 hours.

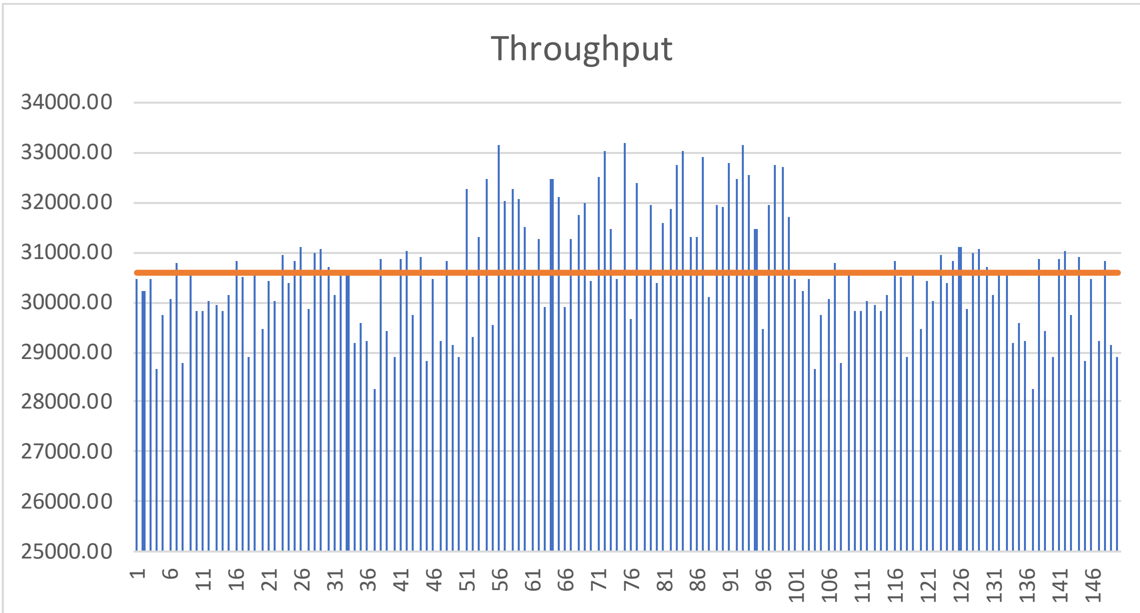

Figure 43: Throughput of Intervention 1

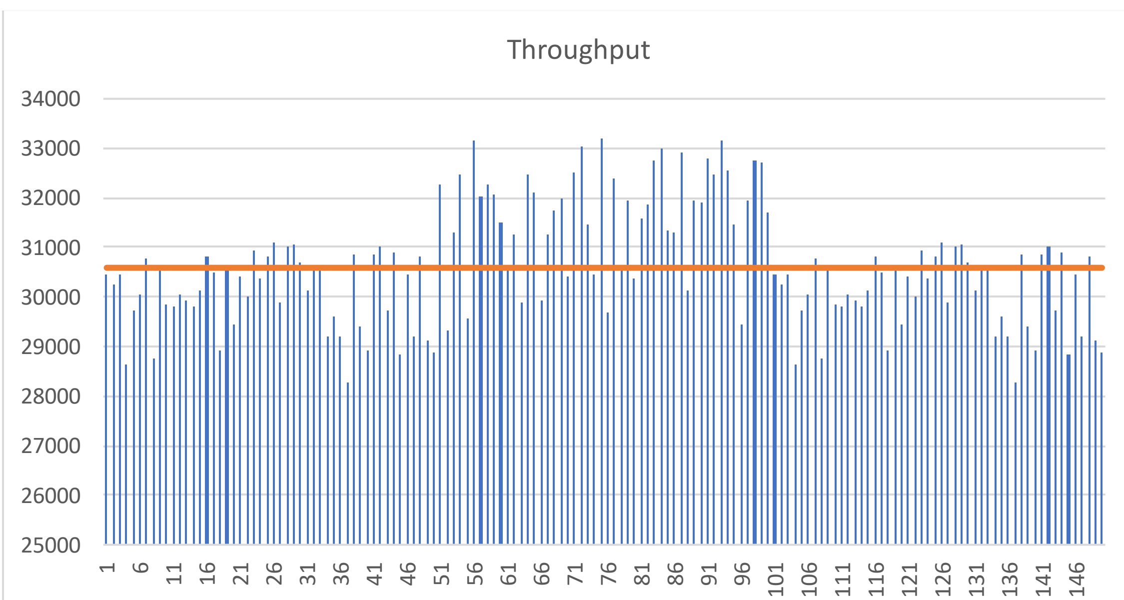

Figure 44: Throughput of Intervention 2

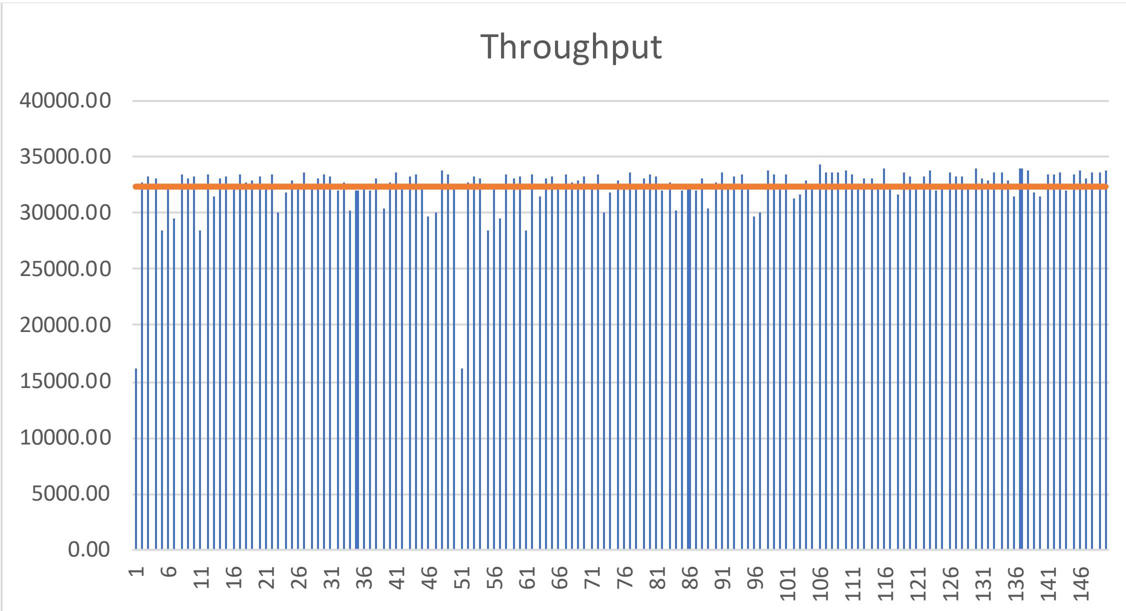

Figure 45: Throughput of Intervention 3

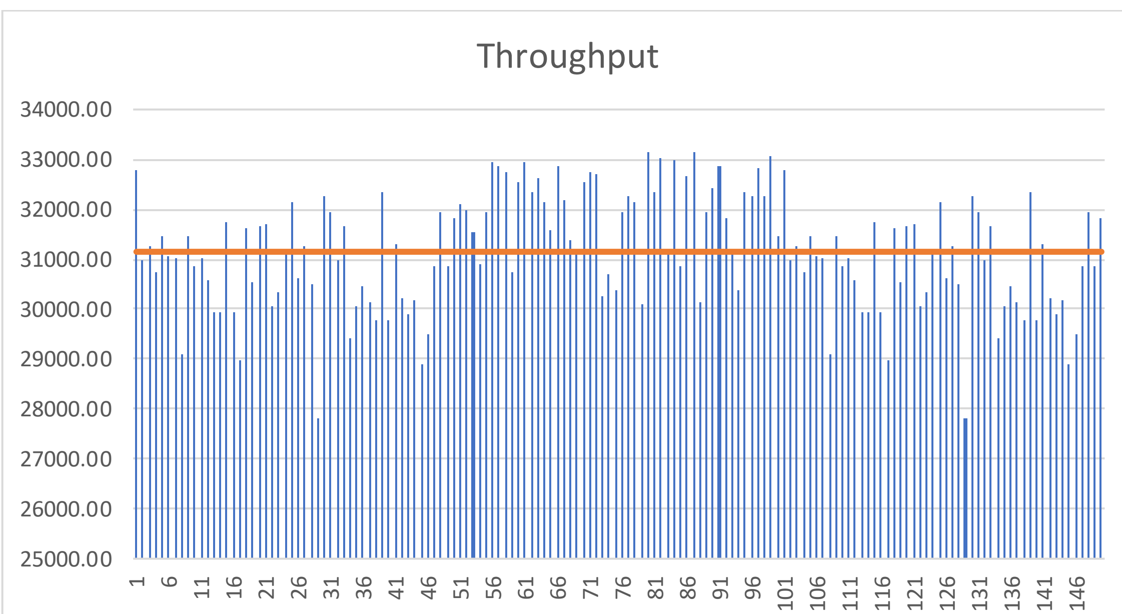

Figure 46: Throughput of Intervention 1+2

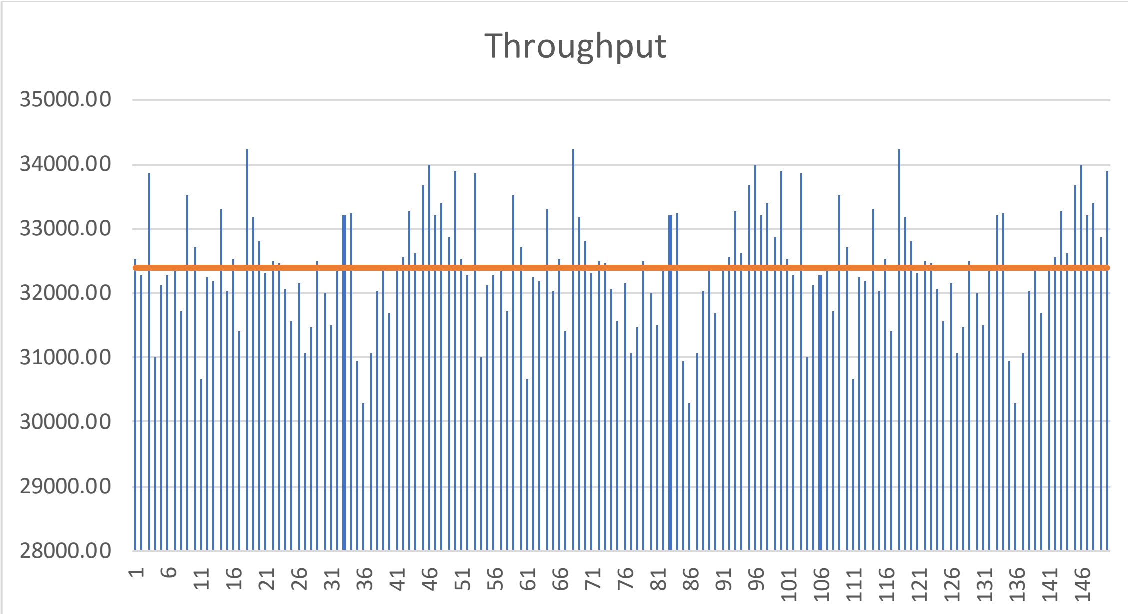

Figure 47: Throughput of Intervention 1+3

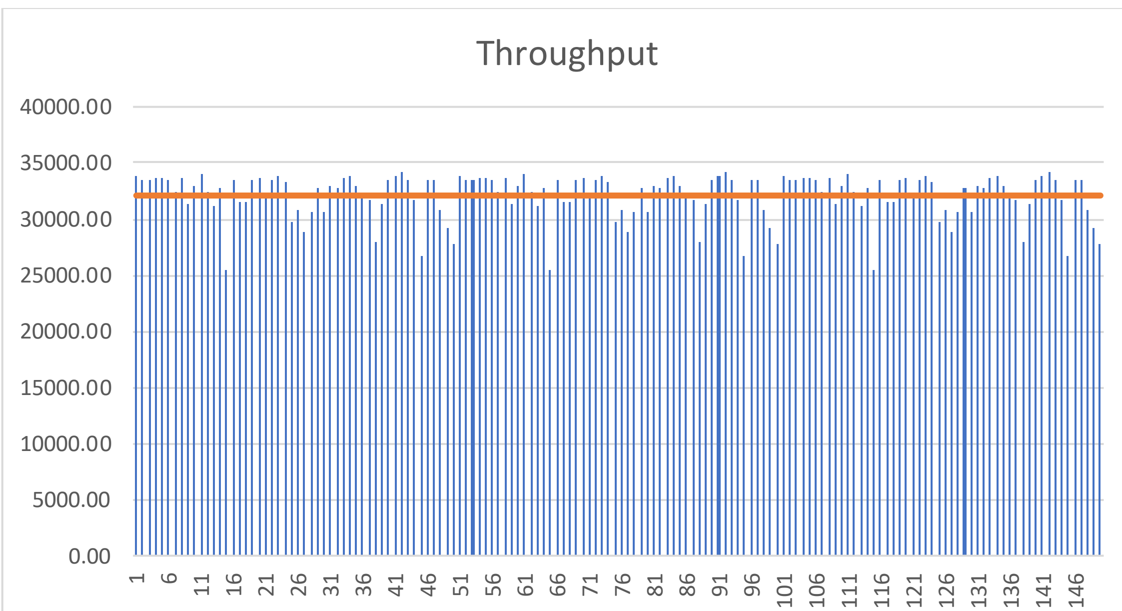

Figure 48: Throughput of Intervention 2+3

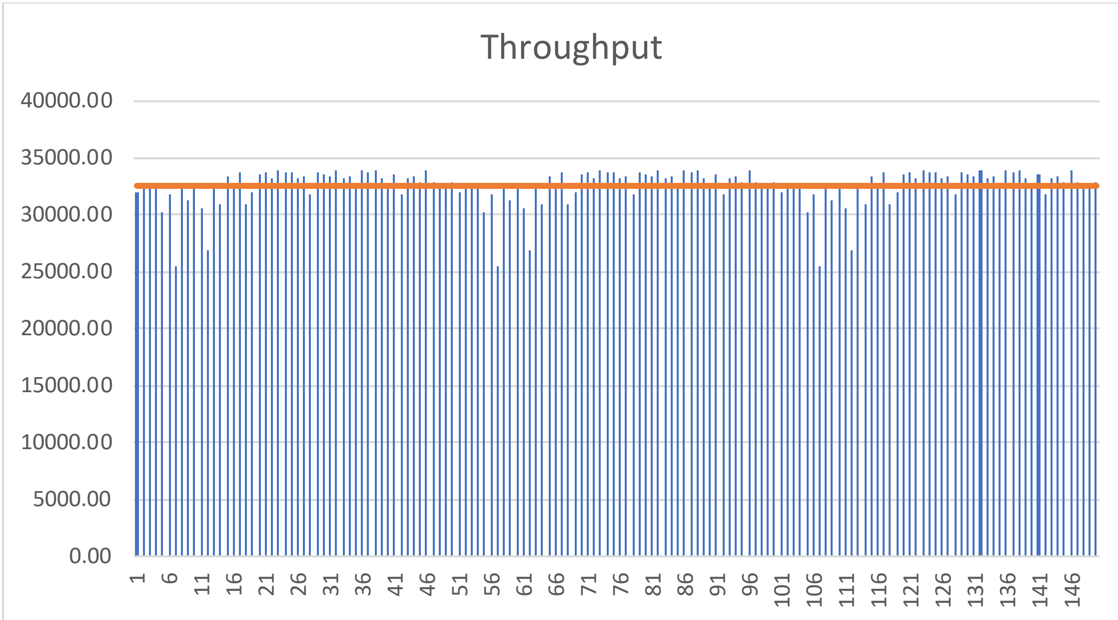

Figure 49: Throughput of Intervention 1+2+3