Enhancing Production Process Efficiency through Value Stream Mapping and Discrete Event Simulation: A Case Study of ECWC-GIW

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Approval Page

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Declaration

I hereby declare that this thesis, entitled “Enhancing Production Process Efficiency Through Value Stream Mapping and Discrete Event Simulation: Case Study of ECWC,” is the result of my own work and research, except where otherwise acknowledged. This work has not been submitted previously, in whole or in part, to qualify for any other academic award. All sources of information and data used have been duly acknowledged.

_____ _____

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List of Abbreviations

ABS - Agent-Based Simulation

DES – Discrete Event Simulation

ECWC-GIW – Ethiopian Construction Work Corporation Geosynthetics Industry Work Plc.

JIT - Just-in-Time

KPIs - Key Performance Indicators

NVA – Non-Value Add Time and Activity

SD - System Dynamics

SLP - Systematic Layout Planning

TPM - Total Productive Maintenance

VA – Value Add Time and Activity

VSM – Value Stream Mapping

WIP – Working in Process

Abstract

The manufacturing industry is increasingly pressured to improve efficiency, reduce waste, and meet rising customer demand in competitive markets. In Ethiopia, the Ethiopian Construction Works Corporation - Geosynthetics Industrial Works (ECWC-GIW) faces persistent production inefficiencies that limit throughput and competitiveness. This study aims to enhance production process efficiency through the integration of Value Stream Mapping (VSM) and Discrete Event Simulation (DES). VSM was applied to map the current production system, distinguish between value-adding (VA) and non-value-adding (NVA) time and activities, and identify bottlenecks. DES was then employed to dynamically model the production process, validate VSM findings, and test improvement scenarios.

The results revealed that the Barrel Vacuum process is the dominant bottleneck, accounting for the largest share of accumulated VA time and constraining system throughput. Additional inefficiencies were identified in the Raw Material Input, Holing, and Cutting processes, which are manual in nature and contribute to delays and waste. Improvement scenarios, including automation of Raw Material Input, workflow layout redesign, and optimization of Holing, Cutting, and Belling Socket, were evaluated using DES. The findings indicated that automation of Raw Material Input alone reduced its mean processing time by nearly 60%, while system-wide improvements increased throughput from 9 tons to 11 tons per day. This represents a 22.22% increase in production capacity, moving the company closer to its production target of 12 tons per day.

The study contributes both theoretical and practical insights. Academically, it demonstrates the complementary strengths of VSM and DES, highlighting their value when integrated for process analysis and improvement. Practically, it provides ECWC-GIW with a structured roadmap for reducing waste, eliminating bottlenecks, and sustaining continuous improvement. More broadly, the findings underscore the applicability of lean-simulation integration as an effective methodology for enhancing production efficiency in developing economy manufacturing contexts.

Keywords: Value Stream Mapping (VSM), Discrete Event Simulation (DES), Lean Manufacturing, Production Efficiency, Ethiopian Manufacturing Industry

Chapter One

1. Introduction and Problem Justification

1.1. Introduction

The manufacturing industry is pilot of an era of rapid change and strong competition. As markets develop and customer demands grow, organizations must continually adapt their processes to remain competitive. Enhancing production process efficiency has become a strategic priority for manufacturers seeking to improve productivity, reduce costs, and achieve increased customers' demands. Efficiency in production processes can be evaluated through key performance metrics such as inventory levels, takt time, lead time, and work-in-process (WIP) levels. These indicators or metrics provide valuable insights into the performance of manufacturing operations, helping to identify bottlenecks, inefficiencies, and opportunities for improvement (Woldemicael et al., 2024).

One of the critical challenges or factors determining the smoothness operation of manufacturing production processes is the optimization of workflows and the effective utilization of resources and production process efficiency. Inefficiencies in production systems, particularly in developing countries, often lead to increased operational costs, delays, and customer dissatisfaction. To address these challenges, innovative tools and methodologies are essential for identifying and eliminating waste, simplifying processes, and enhancing overall productivity. This study focuses on addressing these challenges through the integration of Value Stream Mapping (VSM) and Discrete Event Simulation (DES), these two powerful tools that have best effective in driving production process efficiency optimization.

VSM is a lean manufacturing tool that provides a comprehensive visual representation of production workflows, highlighting inefficiencies and sources of waste. By differentiating between value-added (VA) and non-value-added (NVA) time and activities, VSM offers a clear roadmap for process improvement (Lugert et al., 2018; Narke & Jayadeva, 2020). Complementing VSM, DES enables detailed modeling and evaluation of proposed process changes in a virtual environment. DES provides actionable insights into the potential impact of these changes on efficiency, accuracy,

and overall performance before real-world implementation, reducing risks and costs associated with trial-and-error approaches.

This research applies VSM and DES to the manual raw material input process at the Ethiopian Construction Works Corporation Geosynthetics Industrial Works PLC (ECWC-GIW's). ECWC-GIW's plays an important role in supporting Ethiopia's infrastructure development through its production of essential materials such as PVC and HDPE pipes, geomembranes, and other construction products. However, inefficiencies in its manual raw material input process have created significant challenges in meeting growing customer demands, resulting in delays, increased costs, and reduced competitiveness.

The proposed tools aim to identify specific areas for improvement within ECWC-GIW's production process system, providing actionable solutions to streamline the raw material input process (Lugert et al., 2018). By addressing these inefficiencies, this study seeks to enhance ECWC-GIW's production efficiency, improve its ability to meet increasing market demand, and strengthen its competitiveness in the manufacturing sector. Furthermore, the findings of this research will not only benefit ECWC-GIW but also offer valuable insights for the other manufacturers facing similar challenges, contributing to broader advancement in the manufacturing industry.

1.2. Background

Manufacturing sectors play an important role in providing efficient, effective, and high-quality products to customers. These industries' performance is strongly dependent on their capacity to optimize the production processes, ensuring that resources are used effectively, waste is reduced, and client expectations are addressed efficiently. Efficiency and effectiveness in manufacturing sectors are measured by production process performance, which has a direct impact on product delivery time, customer satisfaction level, and overall profitability of the organization. Improving manufacturing production process efficiency is thus one of the most important parts of assuring the timely delivery of high-quality products to customers.

When the production procedures are inefficient or below capacity the delivery of the product is sometimes compromised. Poor delivery performance compromises not only the profitability and sustainability of manufacturing organization or businesses but also causes consumer dissatisfaction. Customers who are dissatisfied are less likely to

remain loyal, putting the company's long-term viability at risk. In today's competitive market, manufacturing organization must maintain high production process efficiency to be viable and exceed client expectations. To accomplish this, industries use numerous indicators and improvement approaches to identify inefficiencies and apply targeted remedies (Noueihed & Hamzeh, 2024).

The effectiveness and efficiency of manufacturing sectors are directly related to their production process performance. **Waiting time**, **inventory levels**, **work-in-process (WIP)**, and **cycle time** are an important indicator for finding improvement opportunities and presenting effective solutions. These indicators provide essential information on bottlenecks, waste, and inefficiencies, allowing enterprises to optimize processes and increase overall efficiency. For example, excessive waiting time or high WIP levels can suggest inefficiencies in workflow design or resource allocation, whereas high inventory levels can indicate overproduction or poor demand forecasts. Addressing these difficulties through a systematic improvement approach is critical for optimizing manufacturing processes and achieving long-term growth.

In our country Ethiopia, the manufacturing industry has seen remarkable development in recent years, owing to the introduction of contemporary technologies and process optimization approaches. One significant example of this success is Geosynthetics Industrial Works PLC (GIW), which was formed in 2005 as a joint venture between the former Water Works Construction Enterprise and Golden Trade Co. GIW, located in Addis Ababa, Akaki Kality Sub-city, is well-positioned to help the country expand its infrastructure and industrial expansion. The company manufactures a variety of vital items, including PVC-U pipes, HDPE pipes, PP-R pipes, geomembranes (plastic sheets), and rubber seals, as well as related services. These items are critical to Ethiopia's infrastructure projects, particularly the water supply system, electrical conduits, and urban development programs, all of which are critical for increasing living standards and economic growth.

Although these developments have occurred, several Ethiopian manufacturing companies, like GIW, continue to encounter challenges in achieving optimal production efficiency. Manual processes, reliance on human decision, and limited adoption of new technologies frequently lead to inefficiencies, errors, and delays. For example, the GIW manual raw material input process consists of several steps: retrieving goods, weighing, recording, and transporting, which are time-consuming and prone to error. Such

inefficiencies not only raise manufacturing costs but also limit the company's capacity to satisfy rising client demand, which exceeds 300 tons of PVC and HDPE pipes. Addressing these extra needs requires a systematic approach to identifying inefficiencies, eliminating waste, and optimizing production processes.

This study focuses on improving GIW production process efficiency through the use of VSM and DE. VSM is a lean tool for visualizing production processes map and identifying the between value-added (VA) and non-value-added (NVA) time, activities, and operations to discover areas for improvement. DES, on the other hand, allows firms to simulate suggested process modifications and assess the impact on cycle time, work-in-process levels, and overall production process efficiency. By combining these two tools, this study hopes to establish decreasing waste, errors, and optimizing production processes at GIW's, ultimately improving the company's capacity to meet consumer demand and remain competitive in the manufacturing sector.

1.3. Problem Statement

The manufacturing sector is experiencing significant industrialization, with an increasing focus on waste minimization through VSM and simulation technique specially DES. VSM is a powerful lean tool to visualize the processes and identify areas for improvement by distinguishing between VA and NVA time, and activities. Similarly, simulation enhances production process efficiency by modeling outcomes identified through VSM, allowing for the development and prioritization of scenarios. These two approach is important for improving accuracy, reducing production process time, and eliminating waste, defined as any activity that consumes time and resources without adding value to the product (Star, 2016; Woldemicael et al., 2024).

A case study of ECWC-GIW's indicates a critical challenge impacting production process efficiency. The customer demand for PVC and HDPE pipes exceeds 300 tons; however, the company challenges to meet this demand due to significant obstacles. The initial mixing stage of production process on the manual input of raw materials, which involves several inefficiency times and also activities steps: incoming of raw material from mini storage to the measuring area and also the cold mixer, weighing and measuring using scales, manually recording the measured quantities on batch production, and transporting the measured materials to the mixing containers. This multi-step process is time consuming; for instance, handling time of 15 minutes per

batch for manual raw material input. This time, further inefficiency into material returns 3 minutes, weighing and measuring 5 minutes, recording 4 minutes, and transport 3 minutes. This inefficiency underscores the multiple manual raw material input steps contributing to the overall time consumption.

Additionally, the operation dependent on the human decision in measuring and recording quantities increases the risk of errors. A significant issue has the two years from the oversight of not including stabilizer material in the production line that means in hot mixer, which happened approximately once a year. This critical mistake results in substantial production disruptions, leading to the complete halt of operations during the affected batch. The financial repercussions of this error are with material waste estimated at over 800,000 ETB, representing not only lost resources but also potential income. Furthermore, each incident necessitates extensive maintenance and additional checks on the production line to ensure proper functionality, contributing to further downtime and inefficiencies. These cumulative effects highlight the urgent need for improved processes to minimize human error and enhance overall production process reliability.

Moreover, the manual recording of data presents challenges in traceability and data analysis. The depend on paper-based records necessitates manual entry to the company's database, a time-consuming process that introduces further opportunities for transcription errors. This lack of real-time data complicates the identification of trends, affects production process performance analysis, and delays the implementation of timely corrective actions.

The integration of VSM and DES offers a systematic solution to these issues using VSM will provide a clear visualization of the current state, identifying bottlenecks and areas for improvement, and DES will simulate proposed process changes, enabling ECWC-GIW's to evaluate the impact of potential solutions on cycle time, work-in-process levels, and overall production process efficiency. By combining these tools, the organization can develop data-driven strategies to minimize waste, enhance accuracy, and optimize production processes, addressing both immediate inefficiencies and long-term operational challenges.

1.4. Research Questions

- What are the primary inefficiencies and sources of waste in the current production process line?
- How does the time spent on each step of the current process affect the overall production process efficiency?
- How can Value Stream Mapping (VSM) and Discrete Event Simulation (DES) techniques be leveraged to optimize the production process?

1.5. Research Objectives

1.5.1. General Objective

The general objective of this paper is to enhance the production process efficiency in the industry by minimizing waste through the implementation of Value Stream Mapping (VSM) and Discrete Event Simulation (DES) techniques.

1.5.2. Specific Objectives

- To analyze the current production process to identify areas of inefficiency and waste.
- To quantify the time taken for each step of the production process and evaluate its impact on overall production process efficiency.
- To develop and simulate optimized scenarios using VSM and DES to improve accuracy, reduce waste, and enhance production process efficiency.

1.6. Scope and Limitations of The Study

1.6.1. Scope of The Study

This research applies both VSM and DES to improve the production process efficiency at Ethiopian Construction Works Corporation Geosynthetics Industrial Works PLC (ECWC-GIW). The research will study the company's factories by measuring cycle time, lead time and which tasks add value to what does not using the current VSM. As a result of inefficiencies in work processes, equipment and time taken on various production process stage of production. After that, a DES model will help evaluate improvement scenarios for improving production process efficiency before implementing the real world.

This study will offer clear recommendations that help enhancing the production process efficiency in ECWC-GIW's manufacturing areas. The analysis is decided to studying and enhancing production process through simulation, with number of parts that implement to adding ideas into practice. This research identifies production waste and develops improvement scenarios using VSM, then examines these scenarios through DES techniques to develop an optimized or improvement model for enhancing production process efficiency.

1.6.2. Limitations of The Study

Although this study provides valuable insights into improving production process efficiency through the integration of VSM and DES, several limitations should be acknowledged.

First, the research was conducted as a single case study within one production line of the ECWC-GIWs. While the findings are directly relevant to the case company, the results may not be fully generalizable to other industries or contexts without adaptation.

Second, the scope of process coverage was limited to selected stages specifically, Raw Material Input, Cutting, and Holing. Although these processes were chosen due to their inefficiencies and critical role in the production flow, other stages (e.g., mixing, extrusion, and packaging) were analyzed at a higher level of abstraction. This means that some detailed inefficiencies outside the focus area may not have been fully captured.

Third, the data collection process relied heavily on direct observation and time studies. While efforts were made to ensure accuracy, human observation is prone to error, and some process variations may not have been fully reflected in the dataset.

Fourth, the DES model assumptions represent another source of limitation. The simulation was based on average processing times, fixed resource availability, and assumed reliability conditions. Real-world variability such as machine breakdowns, quality rework, or fluctuating demand patterns was not fully incorporated, which may affect the precision of the simulation outputs.

Finally, the study primarily focused on operational efficiency improvements and did not address broader strategic or organizational factors such as workforce skills, supply chain disruptions, or financial cost-benefit analysis of the proposed scenarios. Including these dimensions would provide a more holistic evaluation of improvement strategies.

1.7. Significance of The Study

The research suggests that applying VSM and DES together in the best way to improve production process efficiency. this research studies only batch production systems to fill gap left by previous studies that have commonly presented job shop or continuous systems. Combining these two approaches, the study helps manufacturers identify areas where they can improve, experiment with solutions and make data-supported changes.

VSM supports detailed review of production methods by distinguishing between useful and useless activities. The analysis reveals important delays and unnecessary use of materials in the manufacturing process. After that, using simulation, manufacturers can examine how potential changes might impact their products without physically making the changes. Merging the two approaches makes the process safer and cheaper, compared with just making changes through trial and error.

This work focuses on solving typical batch production issues by adjusting changeover, handling WIP inventory and finding methods for flexible scheduling. The technique gives production managers practical ways to check various operational choices, see their impact on core results and decide on the most successful solutions. The framework can be applied to many types of manufacturing industries that rely on batch production.

The findings illustrate that applying simulation modeling to VSM helps improve lean manufacturing methods. By combining these two methods, business can achieve much better results in process improvement. These study results are especially important for manufacturing operations aiming to make production more efficient without giving up the flexibility needed in batch production.

1.8. Organizations of The Study

This paper is organized into five chapters. The first chapter covers the introduction, including the background of the study, the problem statement, research questions, general and specific objectives, the scope and limitations of the paper, the significance of the study, and the organization of the paper.

Chapter two focuses on the literature review, which includes the introduction, literature review methodology, an overview of lean manufacturing and simulation techniques, VSM, DES, production process efficiency, production process indicators, and a summary of the literature review.

Chapter three presents the research methodology, covering the introduction to the methodology, research design and approach, data collection, ethical considerations, primary and secondary data collection methods, data analysis, methodology framework, and methodology summary.

Chapter four discusses the results and includes the introduction, results, and discussion. Chapter five presents the conclusion and recommendations, followed by the last references and annex at the end of the paper.

Chapter Two

2. Literature Review

2.1. Introduction

The literature review examined a wide range of studies addressing production process efficiency, with a particular focus on lean manufacturing methodologies, especially Value Stream Mapping (VSM), and simulation-based techniques, with a special emphasis on Discrete event Simulation (DES). The review provides a comprehensive overview of existing approaches, tools, and factors influencing efficiency in production environments. Emphasis is placed on the challenges organizations face the benefits of implementing lean and simulation practices, and emerging trends in the field. Specially attention is given to DES-driven solutions, which are increasingly recognized for their ability to model and optimize complex production systems. This literature review also includes an analysis of relevant case studies that demonstrate practical applications and outcomes of VSM and DES. Through this important critical examination of the literature, the study aims to offer valuable insights and deeply understanding of effective strategies for enhancing production process efficiency methodology development, particularly with in the context of Ethiopian Construction Works Corporation Geosynthetics Industrial Works PLC (ECWC-GIW's).

2.2. Literature Review Methodology

The primary objectives of this literature review are important examination existing studies related to production process efficiency, with a particular focus on the indicators, methodologies, and improvement approaches associated with VSM and DES. The review aims to contribute to academic literature in the industrial engineering filed and provide a foundation for future research aimed at optimizing production processes efficiency.

To ensure the relevance and quality of the reviewed literature, a comprehensive search strategy was employed using various academic databases, tools, and search engines. This included Google Scholar, Directory of Open Access Journals (DOAJ), Connected Papers, and the implementing search engines like Google, which were used to access reputable academic databases such as ScienceDirect, Scopus, Emerald, IEEE, SAGE, SpringerLink, Wiley Online Library, and Taylor & Francis. In this research, a total of

58 (49 articles, 1 thesis, 4 conference papers, and 4 books). The inclusion of these materials was based on their direct related to the research objectives that enhance production process efficiency. The selection process primarily targeted publications from 2020 to 2025, reflecting the most recent advancements in the application of VSM and DES. However, earlier studies that provided foundational knowledge or theoretical frameworks were also important. Keywords such as VSM, production process efficiency, DES, lean manufacturing, simulation, lean production, and lean methodology were used to filter and identify relevant literature. Articles were selected based on a primary review of their titles, abstracts, and keywords to assess alignment with the research objectives, and only studies published in English were considered for inclusion.

The findings from the selected literature were synthesized and analyzed to map the current state of the research, identify existing gaps, and highlights opportunities for further study. This review thereby provides a structured and informed basis for understanding how VSM and DES can be effectively solved to enhance production process efficiency, with implications for both academic research and industrial practical solution.

2.3. Production Process

The production process plays a foundational role in the profitability and long-term sustainability of manufacturing industries. It encompasses the complete transformation journey of raw materials into finished products, beginning with the input of raw materials and continuing through each stage of manufacturing until the final products are stored or dispatched. In the context of this study, the production process refers specifically to the manufacturing of PVC-U pipes from the initial raw material input to the final output at the end of the product line.

A well-structured and efficient production process is essential for achieving operational excellence and minimizing costs of the manufacturing industry. According to Noueihed and Hamzeh (2024); and Woldemicael et al. (2024), identifying inefficiencies within the production process efficiencies is important for improving overall performance and ensuring continuous improvement. To this case, VSM, a key lean manufacturing tool, is frequently utilized to visualize, analyze, and enhance or optimize production process workflows.

VSM is instrumental in mapping the current state of the production process, highlighting VA and NVA time and activities, and identifying various forms of waste. These waste elements include excessive waiting times, delays in raw material measurement, unnecessary transportation, and return of unused materials to production mini stores (Emekdar et al., 2023; Klimecka-Tatar & Ingaldi, 2024; Noueihed & Hamzeh, 2024). By identifying such inefficiencies, VSM enables manufactures to design a more streamlined and efficient future state process.

Moreover, enhancing the production process efficiency is directly related to the competitiveness and sustainability of manufacturing organizations. As emphasized by De Oliveira Neves et al. (2024), production process efficiency not only reduces operational costs but also enhances responsiveness to customer demands and supports the long-term variability of industrial organizations sustainability. therefore, placing a strong focus on analyzing and refining production processes efficiency is important for organizations seeking to maintain profitability, reduce waste, and operate sustainability in an increasingly competitive manufacturing market.

2.4. Production Process Efficiency

Production process efficiency is an important key of performance measuring term in the manufacturing industry. It reflects the effectiveness with which inputs such as labor, materials, and equipment, including resources are transformed into high-quality products. Efficiency is typically measured using a combination of quantitative and qualitative metrics, including production output, cycle time, customer satisfaction, delivery reliability, cost effectiveness, and quality of the product (Bhadu et al., 2022; Huynh et al., 2020; Sikander et al., 2024).

In the context of lean manufacturing term, production process efficiency is often analyzed using both dependent variables and independent variables. According to Hardcopf et al. (2021), dependent variables represent the outcomes or performance indicators of the production process system, while independent variables refer to the lean practices or improvement techniques applied to influence those outcomes.

- Dependent variables typically include production performance indicators such as cost of the overall production, quality of the product, delivery time or time taken of the manufacturing, and flexibility of the manufacturing. These dimensions are used to assess how efficiently and effectively a manufacturing

plant operates. For instance, metrics like on time delivery performance, unit manufacturing cost, and product defect rates are used to benchmark the performance of a production facility against industry standards.

- Independent variables, in contrast, encompass lean production practices designed to improve production process efficiency and reduce waste. These include tools and principles such as pull systems (e.g., Kanban), flow optimization, setup of the manufacturing time reduction, and total productive maintenance (TPM). The use of such practices is intended to increase processes, minimize NVA time and activities, and enhance overall productivity.

In the current study, production process efficiency, delivery time, product cost, and other performance related metrics are treated as dependent variables representing the outcomes to be optimized. The independent variables are the improvement techniques applied, specifically VSM and DES. VSM is employed to visualize the entire production flow, identify sources of waste, and important opportunities for production process improvement. DES, allows the development of simulation models that replicate the production process before implementing real world environment. This enables the testing and evaluation of improvement strategies under various scenarios before real-world implementation (Loacker et al., 2024; Karbasi et al., 2024; Khalid et al., 2024).

The integration of VSM and DES provides a powerful approach for enhancing production process efficiency, while VSM helps identify inefficiencies and redesign workflows, DES enables validation of proposed changes, reduces implementation risk, and support data-driven decision-making (Hardcopf et al., 2021; Karbasi et al., 2024; Sikander et al., 2024).

2.5. Production Process Efficiency Problems and Indicators

In the manufacturing organization or industry, various operational metrics are implemented to asse production process efficiency and overall performance. Key indicators or metrics such as product output, cycle time, defect rate, work in process (WIP), inventory levels, travel distance, and performance calculations are widely adopted to monitor and improve production outcomes (Bhadu et al., 2022; Sánchez et al., 2023). These performance indicators serve as essential tools for evaluating how effectively a manufacturing system converts inputs into high-quality outputs, while also identifying bottlenecks and sources of inefficiency.

In this research, a set of Key Performance Indicators (KPIs) has been selected to evaluate and enhance the production process efficiency within the PVC pipe manufacturing sector These KPIs are defined as follows:

- Product Output: This refers to the total number of PVC pipes produced that meet predefined quality standards and are capable of performing effectively in their applicable or intended applications. It is the direct measure of manufacturing throughput and process capacity.
- Cycle Time: The time required to manufacture a single unit form the beginning of the manufacturing to the end of the production process, excluding non production related times such as stock holding time, service interruptions, or installation delays. Shorter cycle time generally reflect a more efficiency production process.
- Product Defect: The number of non conforming products that fail to meet the specified quality requirements. A high defect rate signals inefficiencies and quality issues with in the production process line that require corrective action.
- Work in Proce ss (WIP): Represents the quality of partially completed products currently on the production process line. More WIP may indicate unbalances in the workflow or bottlenecks that slow down production and increase lead times.
- Inventory Levels: The quantity of raw materials, components, and finished goods take at any given time. Managing inventory efficiently are important for maintain smooth operation without incurring unnecessary holding costs.
- Distance: Refers to the physical distance traveled during the production process, including the movement of materials from storage areas to production lines and between different workstations. Long travels distances can contribute to inefficiencies and increased labor inefficiencies or transport time.
- Overall Performance: In this study, performance is calculated by subtracting service-related product losses from the sum of inventory, WIP, and defect items. This composite metrics provides insights into the net productive value of the production process.

In addition to the key performance indicators previously discussed, production process time also encompasses several other critical components that influence overall efficiency. these include setup time, rework time idle time, and other operational delays that may occur throughout the production process cycle increased. Such elements are

essential for gaining a more comprehensive understanding of manufacturing performance, as they directly impact cycle time and resource utilization.

Loacker et al. (2024) emphasize the significance of these time based variables in assessing production process efficiency. Their study demonstrate that inefficiencies related to setup and rework can contribute to performance current and improved system ranging between 1.98% and 5.19% of total production time, as illustrated in Figure 1. These findings highlight the importance of not only measuring output of the product and defects but also capturing detailed time metrics to identify hidden inefficiencies with the production process system.

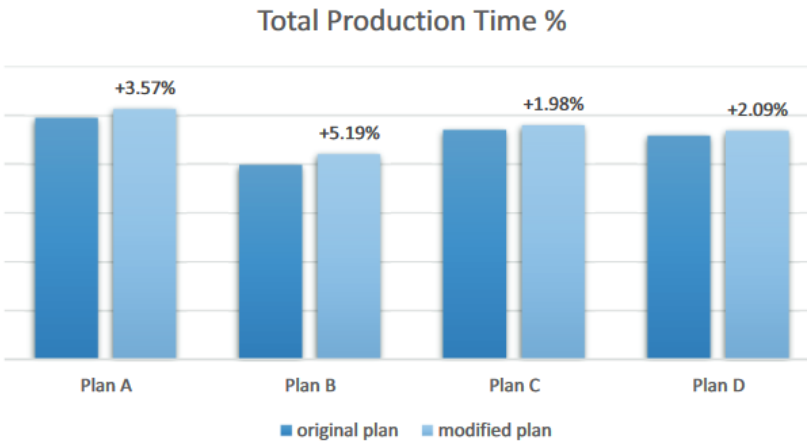


Figure 1 Production Time Source (Loacker et al., 2024)

Therefore, incorporating time-based metrics into the analysis provides a more holistic evaluation of production process efficiency. It also justifies the use of simulation tool such as DES, which allows for the modeling of such time related variables and helps to forecast the impact of potential improvements prior to implementation. These KPIs are critical for accurately assessing the efficiency of the PVC pipe production process. They enable a detailed analysis of time usage, product volume, and quality levels. All of which are fundamental to ensuring operational performance. By applying these indicators, the research identifies performance gaps and areas for improvement in the current system, providing the implementation of lean techniques such as VSM and simulation techniques such as DES.

2.6. Production Process Efficiency Improvement Techniques

Manufacturing industries implement a wide range of techniques to improve production process efficiency, reduce waste, and enhance the organization competitiveness.

Among the most widely applied approaches are lean based methods such as VSM and simulation techniques such as DES, as well as established practices including SMED, Kaizen, Kanban, and automation strategies.

VSM is a lean manufacturing tool designed to visualize, analyze, and map material and information flows across the production system. By distinguishing between VA and NVA activities, VSM provides a clear picture of where inefficiencies exist and serves as a foundation for designing targeted improvement scenarios (Aksar et al., 2022; Batwara et al., 2024; Bhadu et al., 2022; Narke & Jayadeva, 2020; Star, 2016; Wang et al., 2024). However, VSM alone is limited in predicting futural of the dynamic impact of these changes under real operating variability.

To overcome this limitation DES is often integrated with VSM, while VSM identifies and categorizes inefficiencies, DES enables experimentation by testing, validating, and comparing alternative improvement scenarios in a simulation techniques environment before real world implementation. This integration reduces the risks of trial-and-error approaches in real systems and provides quantitative evidence for decision making (Aksar et al., 2022; Kelton et al., 2015; Loacker et al., 2024; Woldemicael et al., 2024). Other techniques also play a critical role in improving process efficiency. SMED focuses on reducing setup and changeover times, enabling more flexible production and smaller batch sizes (Emekdar et al., 2023). Kaizen emphasizes continuous improvement driven by employee involvement, while kanban regulates material flow through pull-based systems, thereby minimizing inventory levels and overproduction (Emekdar et al., 2023). Automation and digital technologies further complement these methods by enhancing precision, reducing manual errors, and improving consistency.

This study, however, specifically focuses on the integration of VSM and DES as the core efficiency improvement techniques. The rationale for this choice is two terms: first, VSM allows the identification of waste and bottlenecks across the production process line; and second DES provide a dynamic improvement scenarios testing, data driven means of evaluating proposed solutions. Together, they form a powerful methodology to determine which scenarios yields the best performance improvements before implementation in the real-world production process environment.

2.7. Value Stream Mapping and Discrete Event Simulation

2.7.1. Value Stream Mapping

Enhancing production process efficiency is an important term in the manufacturing industry, and Value Stream Mapping (VSM) is one of the most important tools used to achieve this goal. VSM enables the visualization and evaluation of current production workflows, highlight VA and NVA time and activities. It supports the development of future state maps that cover as improvement blueprints for increased operations and eliminating waste (Noueihed & Hamzeh, 2024; Woldemicael et al., 2024).

As a basic component of lean manufacturing, VSM is part of a broader strategy aimed at maximizing customer value by minimizing resource consumption. Lean manufacturing originated in the 1920s within the automobile industry, primarily to eliminate waste and improve production process efficiency (Buer et al., 2021; Saad et al., 2024; Wang et al., 2024). Over time, it has evolved into a comprehensive management philosophy focused on continuous improvement, quality enhancement, and sustainability. It aims to reduce NVA time and activities, optimize workflows, and improve key performance metrics to enhance competitiveness and long term viability (Adeyemi et al., 2021; Emekdar et al., 2023; Goshime et al., 2019).

According to Emekdar et al. (2023), lean manufacturing promotes efficiency and profitability by reducing waste, improving product quality, lowering operational costs. This two focus on performance and sustainability supports customer satisfaction and provides company with a competitive advantage. Lean thinking emphasizes a continuous improvement mindset, employe involvement, and the systematic removal of all forms of waste commonly referred to as *Muda* in Japanese. Ohno & Bodek (2019) identified seven types of waste that lean seeks to eliminate overproduction, waiting, transportation, overprocessing, excess inventory, unnecessary motion, and defects (Wang et al., 2024; Yang et al., 2025).

To achieve its objectives, lean manufacturing employes a wide range of tools and techniques. Among the most widely used tool in the manufacturing industry but not limited in the manufacturing industry both service industry are **Just-in-Time (JIT)** (Batwara et al., 2023), **Single-Minute Exchange of Dies (SMED)** (Ortega et al., 2022), **Total Productive Maintenance (TPM)** (Saraswat et al., 2024; X. Yang et al., 2025), **Kaizen** (Soliman et al., 2022), 5S (Emekdar et al., 2023; Pirrone et al., 2024), and **Value Stream Mapping (VSM)** (Noueihed & Hamzeh, 2024). These tools are often used in combination on the specific challenge of the production process system. For instance, VSM is frequently integrated with simulation techniques such as Discrete

Event Simulation (DES) to model and evaluate improvement scenarios before implement the real world practice.

VSM plays a foundational role in lean initiatives. It provides a detailed visual representation of the flow of materials and information throughout the production process, enabling organizations to identify inefficiencies (Batwara et al., 2024) and areas for improvement (Keykavoussi & Ebrahimi, 2020; Moreira & Silva, 2021; Saad et al., 2024). As Noueihed & Hamzeh (2024) explain, VSM enhances process visibility and serves as a strategic tool for lean execution. It not only identifies VA and NVA steps but also enables companies to measure critical metrics such as cycle time, lead time, inventory levels, and resource usage (Kashyap et al., 2025; Maryadi et al., 2024).

Moreover, VSM is considering a dynamic improvement tool that assists in the development of future state maps production process redesigns that eliminate waste and optimize efficiency, by providing a comprehensive overview of the production process flow, including bottlenecks, redundancies, and delays, VSM supports evidence-based decision-making and fosters alignment among stakeholders (Al-Aomar et al., 2015; Gopi et al., 2020; Heravi et al., 2021).

In this study, VSM is used to evaluate and improve the production process of PVC pipe manufacturing. The tool is highly effective in mapping the current state of the production process, identifying inefficiencies, and designing improvement scenarios. By distinguishing between VA and NVA activities, the company can develop targeted interventions to reduce delays, minimize excess inventory, streamline workflows.

Woldemicael et al. (2024) emphasize that VSM development incorporates a range of essential metrics including **changeover time**, **work-in-process (WIP)**, **cycle time**, **inventory levels**, **lead time**, **waiting time**, **VA and NVA time and activities**, **output rates**, and **manpower requirements**. These parameters are central to diagnosing the current state of production and developing actionable strategies for performance improvement.

VM uses standardized symbols and notation to represent various components of the production process system (Vamsi Krishna Jasti & Sharma, 2014). These symbols include representations for suppliers and customers, inventory, production operations, material flows, and timeframes. Each symbol plays a role in accurately modeling the production process, making the resulting production process map easy to interpret and

useful for collaboration and improvement planning. For examples, the inventory symbol indicates stock between operations, while the supplier or customer symbol mark input or output points in the value chain. These symbols are applied in this research to facilitate analysis of the PVC pipe production process at the case company, with a focus on identifying and reducing NVA time and activities.

2.7.2. Discrete Event Simulation

Discrete Event Simulation (DES) is a widely used simulation modeling and analysis technique for representing and evaluating the behavior of complex systems whose states change at specific, discrete points in a time (Thenarasu et al., 2024). It models the systems as a sequence of events, each occurring at a particular moment, to reflect changes in the system's state and flow (Ardalani et al., 2024; Cubukcuoglu et al., 2020). DES enables researchers and practitioners to explore system behavior under varying conditions by simulating alternative configurations, testing improvement scenarios, validating solutions, and ultimately enhancing performance. These features make DES a powerful tool for analyzing dynamic, complex manufacturing systems (Heravi et al., 2021; Huynh et al., 2020).

The primary objective of DES apply in this research is to **enhance process efficiency** by enabling performance evaluation before real-world implementation. Through modeling and simulation, the case company or the organizations can experiment with different process structure, resource allocation, and policies without disrupting actual operations (Huynh et al., 2020). DES is therefore instrumental in increasing organizational effectiveness by reducing risks, improving decision-making, and optimizing system performance.

Simulation plays an important role in supporting **lean manufacturing initiatives** by allowing stakeholders to visualize and assess real-time performance and develop improvement strategies grounded in emphatical evidence. Saraswat et al. (2024) note that simulation has become in both manufacturing and service sectors, offering applications across industries such as healthcare, aviation, logistics, and also education. In manufacturing contexts, simulation enables the modeling of real-world production process challenges including process variability, resource constraints, and demand fluctuations.

Simulation is broadly defined as the use of models to duplicate the structure and behavior of real systems over time. These models are often developed using **specialized software tools** and executed on computers to assess system behavior, test modifications, and predict outcomes (Robinson & Brooks, 2024). According to Kelton et al. (2015, pp. 7 - 8), simulations can be categorized along three key dimension or pats:

1. **Static vs Dynamic**: Static simulations represent systems where time is not a significant factor (e.g., probabilistic estimation problems), while dynamic simulations account for the evaluation for systems over time such as those in production environments.
2. **Continuous vs Discrete**: Discrete simulations focus on systems where state changes occur at specific points (events), such as task completions or arrivals. Continuous simulations, on the other hand, model systems with smooth, ongoing change over time, often requiring differential equations.
3. **Deterministic** vs **Stochastic**: Deterministic models assume non randomness in inputs or behavior, but Stochastic simulations incorporate uncertainty reflecting the variability and randomness observed in real-world operations or data.

In addition to these clarifications simulation methodologies can be grouped into **Discrete Event Simulation (DES)**, **Agent-Based Simulation (ABS)**, **and System Dynamics (SD)**. Hybrid models that combine these approaches such as DES with ABS or DES with system dynamics (SD) (Bottani & Casella, 2024; Kar et al., 2024).

This research adopts a dynamic, stochastic DES model for three key reasons:

1. The production process at the case company of ECWE-GIW is normally dynamics,
2. DES provides the most appropriate modeling structure for representing such as systems and,
3. A stochastic approach is necessary to account for variability in production process cycle time, resource availability, and other operational factors (Noueihed & Hamzeh, 2024).

The data for the DES model are derived from the VSM outputs and the VSM data observed and historical production performance, particularly cycle time, WIP levels, and waste metrics. These are used to calibrate the simulation and ensure it accurately

reflects the real-world production environment. As Al-Aomar et al. (2015) emphasize, simulation should be used to test and refine improvement strategies before implementing them operationally. This approach supports lean implementation by minimizing disruptions and increasing the likelihood of success.

Among various DES tools, Arena is one of the most widely adopted simulation platforms for modeling and optimizing industrial systems (Verawati et al., 2024; Hossain et al., 2023). In this study, Arena is employed to construct the DES enables the modeling of various "what-if" scenarios such as reducing setup time, reallocating resources, and minimizing idle time. All of which are critical for enhancing the production process.

DES operates through fundamental components:

- Entities (e.g., PVC resin, Calcium carbonate, Stabilizer, Titanium dioxide, Coloring pigments like carbon black, orange pigment, yellow pigment or other, and Stearic acid and wax if the calcium carbonate is uncoated)
- Attribute (e.g., 160, to 400mm dimeter by 6m length)
- Resources (e.g., Hot mixer, Cold mixer, Extrusion, Barrel vacuum, Vacuum tanker, Cooler tanker, Hole, Cutting, and Beling and also including workers), &
- Events (e.g., production process time or job completion or material arrival)

The simulation progresses chronologically, updating the system's state with each discrete event (Brentnall, 2007; Kelton et al., 2015). This method is particularly well-suited for manufacturing, as it can capture real-time process dynamics, identify bottlenecks, and evaluate system-level performance improvements.

The process of building a DES model generally follows a multi-step approach:

1. Simulate the current-state model based on the real-world process data,
2. Assign system parameters and constraints such as resources, production process cycle times, and the process capacities,
3. Validate the model through comparison with production process outcomes,
4. Test multiple improvement scenarios, and
5. Redesign the production process map to reflect the optimal future-state configuration.

In this research, the DES model is used to evaluate and improve the PVC pipe production system at ECWC-GIW's. The simulation focuses on reducing non-value-

added activities, minimizing WIP and production cycle time, and improving overall output. The combined use of VSM and DES supports a holistic improvement strategy: VSM identifies waste, while DES enables the testing and validation of proposed changes in a risk-free virtual environment (Hidayat et al., 2024; Li et al., 2023).

DES offers a powerful method for modeling, analyzing, and improving complex manufacturing systems. Its integration with lean tools such as VSM enhances the ability to detect inefficiencies, assess potential solution, and drive continuous improvement. By simulating various process configurations and identifying optimal setups before real-world implementation, DES supports data-driven decision-making and enhances both efficiency and operational resilience.

Finally, the important topic of the DES modeling, selecting an appropriate probability distribution for the input parameters such as process time, waiting time, or interarrival time is essential for accurately representing system variability. The **Gamma probability distribution** was chosen in this study due to its practicality, simplicity, and suitability in situations where detailed statistical data is limited but reasonable estimates.

According to Kelton et al. (2015), processing times in manufacturing systems are non-negative and typically right skewed due to operational variability, making the Gamma distribution a suitable choice for input modeling in discrete event simulation.

Gamma probability distribution model construction formula: - (Hoad et al., 2010; Law, 2015)

$$GAMMA(BETA, ALPHA)$$

Model verification of both the current and improved models, the replication number and length: - (Hoad et al., 2010; Law, 2015)

$$Replication\ Lenght = Shift\ Lenght * Number\ of\ Shifts$$

$$Replication\ Number = \left(\frac{t - value\ or\ confident\ level * standard\ deviation\ of\ pliminary\ output}{desired\ half\ width\ of\ the\ confident\ level\ interval}\right)^2$$

In this research, 20 replications were applied for the following commonly recommended rule of the replications should be between 20 and 30. So, the selection is rule based.

Gamma distribution provides a flexible and statistically robust representation of processing time variability, particularly under limited data conditions (Tyworth, 2025; L. Yang et al., 2025). Therefore, in this study, the **Gamma distribution** was applied to represent uncertain process time data within the production process system. This choice aligns with established simulation practices in estimation under uncertainty while maintain model simplicity and clarity.

2.8. Literature Review Summary

The integration of these two tools or techniques VSM and DES has gained recognition as an effective approach for optimizing manufacturing production processes. Recent studies demonstrate the versatility of these methods across various industries, through significant gaps remain in their application to batch production systems, particularly in PVC-U pipe manufacturing sectors.

Ardalani et al. (2024) successfully implemented DES for modular construction sector optimization, achieving reliable productivity improvement. However, their findings in the construction sector don't translate to manufacturing environments. Similarly, Sánchez et al. (2023) demonstrated the effectiveness of lean tools in construction, but their continuous improvement methods require adaptation for batch production systems. In the automotive sector, Aksar et al. (2022) combined VSM with simulation techniques, providing valuable financial analysis methodologies, through their focus on assembly lines differs substantially from batch production requirements.

The food industry offers relevant insights, with (Loacker et al., 2024) applying DES to optimize production processes, through their work overlooks the thermal constraints critical to PVC manufacturing. Bhadu et al. (2022) contribute significantly by developing lean performance indicators for SMEs, particularly in waste elimination, but their approach lacks the simulation component needed for predictive analysis in batch environments or batch production systems.

Current research reveals several limitations in addressing PVC-U pipe production challenges. Woldemicael et al. (2024) applied VSM and DES in leather manufacturing but used static, liner models that fail to capture the dynamic nature of batch production. Noueihed & Hamzeh, (2024) focused narrowly on shopfloor-level analysis, missing opportunities for system-wide optimization. Notably absent from existing literature is any comprehensive treatment of diameter dependent process variations (160-400 mm

pipes) and thermal constraint (hot mixing at 116^0C, vacuum processing at 100^0C) that characterize PVC-U Manufacturing.

This study addresses these gaps by developing an integrated VSM-DES framework specifically for PVC-U pipe production. The research builds on existing methodologies while introducing dynamic modeling of batch transitions and thermal processes. By combining VSM's waste identification capabilities with DES's predicative scenario testing, the approach offers practical solutions for optimize changeover time, reducing raw material input process, bottleneck, and improve production process. The resulting farmwork provides both theoretical advancement in batch production optimization and actionable implementation guidelines for PVC-U manufacturers seeking to balance efficiency gains with restrictive quality requirements.

Chapter Three

3. Research Methodology

3.1. Introduction

The methodology section of this paper presents various essential components, including the research design and approach, data collection methods, data analysis techniques, framework, and a summary of the methodology, with a specific focus on the production process efficiency.

3.2. Research Design and Approach

This study employs an experimental and explanatory research design that focuses on integrating Value Stream Mapping (VSM) and Discrete Event Simulation (DES) techniques to optimize production process efficiency. The explanatory research part is focus on the development of the process map, value stream mapping and also the development of the impressment scenarios from the output of the value stream mapping, and the simulation is utilized as an experimental method to model the current production process, identify areas for improvement, develop enhancement scenarios, and validate the model before real-world implementation.

A mixed-methods research approach is adopted, combining qualitative and quantitative methodologies to address the core research questions. Data collection and interpretation incorporate both qualitative and quantitative data to ensure comprehensive insights.

Quantitative Research Approach:

Systematic observations, along with historical data analysis, collect quantitative data for measuring key performance metrics, while dedicated time studies facilitate these measurements. The performance evaluation relies on measurements of cycle time, waiting time, processing time, WIP, VA activities, and along with NVA activities and time, and with other production-related variables. The gathered data enables one, VSM process map construction, two, improvement scenarios development, and three, DES model accuracy verification before actual implementation.

Qualitative Research Approach:

Qualitative data is gathered through semi-structured interviews with frontline workers, managers, and stakeholders, supplemented by a review of relevant journal articles. This

approach provides contextual insights into current production processes, challenges, and potential areas for improvement. Additionally, a direct observation process is conducted to triangulate findings and enhance the validity of the proposed efficiency strategies.

3.3. Data Collection

3.3.1. Ethical Consideration

The research involves collaboration with the production and technical manager, operational manager, and frontline workers to collect data on production process efficiency. Data collection is conducted through informed authorization, ensuring participants fully understand the purpose, procedures, and their right to withdraw at any time. Privacy and confidentiality are prioritized by anonymizing participant identities, securely storing sensitive data, and restricting access to authorized personnel only. Ethical safeguards such as encryption for digital records and secure physical storage for documents are implemented to protect participant information. Throughout the research process, participant autonomy, respect, and privacy are securely kept, aligning with ethical standards for human subject research. All data is used solely for the stated objectives, with results reported in aggregate to prevent individual identification.

3.3.2. Primary Data Collection Methods

In the primary data collection methods, relevant information has been collected for the research. Related data to the objective of the study is collected using the observation method and interviews.

Observation Method:

Observation is a vital primary data collection method that directly involves the researcher. As a systematic approach, observation focuses on watching and recording events in an unbiased studied. During observations of the production process, the researcher concentrated on key metrics such as cycle time, waiting time, processing time or WIP, VA activities and time, NVA activities and time, lead time, and other critical parameters. The data collected or recording only one week continuously and the other data used to historical and also interview methods.

Interview Method:

Interviews are another tool for primary data collection. Related to this research, interview questions that have missed in the observation or recording time they have been prepared question for the frontline workers, production managers, technical managers, and operational managers to useful to the researcher to deeply understand for the process map, and any other operation to support the research directly and indirectly. This is done to evaluate production process efficiency from diverse perspectives. The main points raised in the interviews include: the current state of production process efficiency, workflow challenges, areas for improvement identified by both workers and management, operational constraints, benefits of existing processes, potential solutions for optimization, and strategies for sustaining efficiency in the future.

3.3.3. Secondary Data Collection Methods

Secondary data collection methods have been utilized in this research. The types of secondary data sources explored include historical production records and literature review of related topics. Data gathered from these sources aids in understanding the requirements of the production process, identifying future trends, and analyzing technological advancements in the manual raw material input process. To achieve the research objectives and address the research questions, literature reviews and historical data were strategically selected to ensure alignment with the study's focus on enhancing production process efficiency.

Literature Review:

The literature review is one of the most effective secondary data collection methods. It provides insights into production process efficiency challenges, methods, and applications, as a valuable resource for future researchers and decision makers addressing production process efficiency problems. By examining studies and literature reviews on the topic, data and information about production process efficiency challenges can be gathered, and improvement scenarios can be explored through DES models, various production process efficiency requirements, optimization techniques, and simulation tools.

Historical Data:

These data types represent one of the secondary data collection methods used in this research. While primary data collection methods were employed to gather one week's

worth of data, this was further supported by historical data types. The historical data includes job orders, production process times, and product delivery information, which can be utilized for analysis. For this study, six months of production process history were used to ensure a relevant and comprehensive collection of data on production process efficiency. This document is crucial as it aids in developing improvement scenarios, making informed decisions, and supporting the analysis phase for proposed solutions.

3.4. Data Analysis

In the previous sections, the research employed various data collection methods to gather data and gain insights into production process efficiency, identify trends, and support decision-making. After collecting data using both primary and secondary data collection methods, the next step was organizing and analyzing the data. The process of data organization led to the computation of average times for all variables because historical observation data analysis becomes difficult. The calculated variable averages in Excel served as inputs for **VSM** because of their importance to develop the value stream mapping process.

Data analysis is a critical phase in the research process, as it is used to evaluate, optimize, or enhance the initial points of the study. This phase aims to address the research problem by answering the research questions and objectives. In this case, the analysis focused on evaluating the current production process map, developing the simulation model, and creating improvement scenarios to enhance production process efficiency.

For the primary data collection, observation methods were used to analyze data, which was directly input into VSM. This helped identify improvement areas and waste. The VSM was developed using **Minitab** software, which is user-friendly for creating VSMs and calculating metrics such as cycle time, processing time or WIP, VA activities and time, NVA activities and time, and lead time. However, a limitation of Minitab is that it does not calculate efficiency ratios or cycle ratios, so these were calculated manually. The data collected, along with the development of VSM and the identification of waste and improvement areas, was then used to develop the current simulation model using DES software, specifically **Arena**. **Arena** is a powerful DES tool for visualizing the current model and developing improvement scenarios. Arena software, where the

Gamma probability distribution was assigned to represent process time variability due to known system. These scenarios were prioritized the improvement scenarios to identify the most impactful improvements. The researchers utilized Microsoft Excel Professional Plus 2016 as their software platform. With appropriate input data, this tool allows users to create Pareto charts in a streamlined manner.

For Gamma probability distribution model construction, the following formula was used: -

$$GAMMA(BETA, ALPHA)$$

For model verification of both the current and improved models, the replication number and length were defined as follows: -

$$Replication\ Lenght = Shift\ Lenght * Number\ of\ Shifts = 8 * 23 = 24\ Hours$$

$$Replication\ Number = \left(\frac{\text{t} - \text{value or confident level} * \text{standard deviation of pliminary output}}{\text{desired half width of the confident level interval}}\right)^2 = 20$$

The selection wase rule-based selection.

This process was supported by the secondary data sources, such as historical data and journal articles. Secondary data proved useful in validating findings, providing context, and enhancing the overall analysis. Together, these methods contributed to achieving the research objectives of enhancing production process efficiency through VSM and DES.

3.5. Research Methodology Framework

The research methodology framework outlines the step-by-step process and components required to achieve the research objectives. This framework provides a systematic approach to identifying and developing improvement scenarios for enhancing production process efficiency.

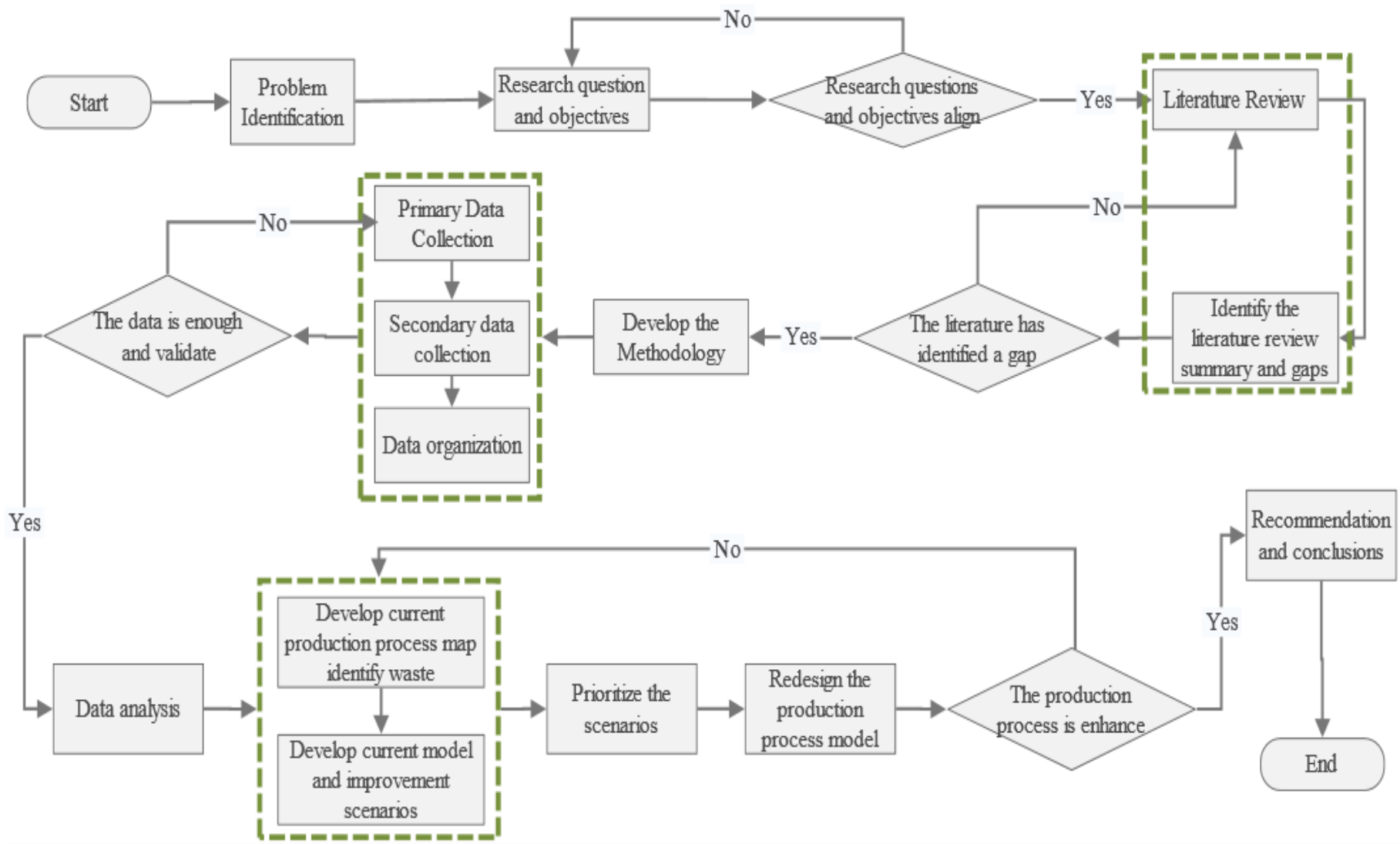


Figure 2 Research Framework

3.6. Research Methodology Summary

Table 1 Methodology Summary

No	Research Questions	Research Specific Objectives	Data Collection Methods (Tools)	Data Analysis Methods
1	What are the primary inefficiencies and sources of waste in the current manual raw material input process?	To analyze the current manual raw material input process to identify areas of inefficiency and waste.	▪ The primary data collection methods utilized both observation and interviews. ▪ Secondary data collection methods supported the research, including historical data and journal articles.	▪ VSM identifies the wastes.
2	How does the time spent on each step of the current process affect the overall production process efficiency?	To quantify the time taken for each step of the raw material input process and evaluate its impact on overall production process efficiency.		▪ Primary data (observation and interviews).
3	How can Value Stream Mapping (VSM) and simulation techniques be leveraged to optimize the raw material input process?	To develop and simulate optimized scenarios using VSM and DES to improve accuracy, reduce waste, and enhance raw material input process efficiency.	▪ Using the output from the primary data analysis phase or the results generated from the VSM.	▪ Develop the process map using VSM and create the current model along with improvement scenarios using DES.

Chapter Four

4. Results and Discussion

4.1. Introduction to Data Collection and Analysis

This section presents the data collected from the case company's production process, including time and capacity measurements, raw material details, and other relevant operational parameters. The primary data was collected through direct observation and on-site supervision, and the secondary data was obtained from historical records and a comprehensive literature review. The historical data was systematically organized by the production team and cross verified with the primary data to ensure accuracy and consistency.

The next phase forms the data collection part to involves a detailed analysis of the collected data, employing **Value Stream Mapping (VSM**) to identify inefficiency and **Discrete Event Simulation (DES)** to model and evaluate potential improvements. The findings are then discussed to assess their implications for enhancing production process efficiency at ECWC-GIW's. This structured approach ensures a data driven optimization strategy, alignment with the research objectives of minimizing waste, reducing cycle times, and improving overall production productivity.

4.2. Case Company Description

Ethiopian Construction Works Corporation Geosynthetics Industry plc. (ECWC-GIW), a joint venture of Ethiopia Construction Works Corporation (ECWC), specializes in manufacturing plastic construction materials including PVC-U pipes, HDPE pipes, and geomembrane sheets. This study focuses on implementing an integrated approach combining the lean tool VSM with the simulation tool DES to improve inefficiencies in the raw material input process.

The company manufactures product of various types and sizes using a batch production system, with the complete manufacturing process spanning from raw material input to belling socket in the PVC-U pipe (see Figure 3). Data for this study was collected through direct observation at the facility as well as analysis of historical records from technical and production department documents.

The research identified significant challenges in the raw material input process of PVC-U pipe, which exhibited multiple inefficiencies affecting overall production

performance. The application of VSM and DES tools proved particularly valuable for: Identifying specific inefficiency points, Developing practical improvement solutions, and Providing knowledge contributions for process optimization. These methodologies offer powerful capabilities for addressing the company's production challenges while minimizing implementation risks through virtual testing of proposed changes.

4.3. Result

4.3.1. Production Process Analysis

4.3.1.1. Process Mapping and Time Observation

The manufacturing process begins with raw material preparation, where PVC resin, calcium carbonate, stabilizers, titanium dioxide, and coloring pigments (e.g., carbon black, orange, or yellow) are blended. If uncoated calcium carbonate is used, it requires additional stearic acid or wax. These materials are then fed into a hot mixer and processed at 116^0C for 15 – 20 minutes; this duration scales with pipe diameter. This thermal fusion ensures homogeneity but creates a bottleneck for larger diameters. (For example. 400 mm pipes occupy the mixer 67% longer than 116 mm pipes.)

The compound then transfers to a cold mixer, where it is cooled to 45^0C for 25 – 30 minutes. This fixed duration stage stabilizes the material for extrusion but limits hourly throughput. The cooled blend feeds into the extrusion line, where a barrel vacuum stage operates at 100^0C for 1 hour per batch a critical constraint that caps Line 1's capacity at 12 tons/day.

Post-extrusion, pipes undergo calibration in a vacuum tank, water colling (with duration proportional to wall thickness), precision cutting, and belling socket forming. See Figure 3 for the detailed process map of the PVC-U production process.

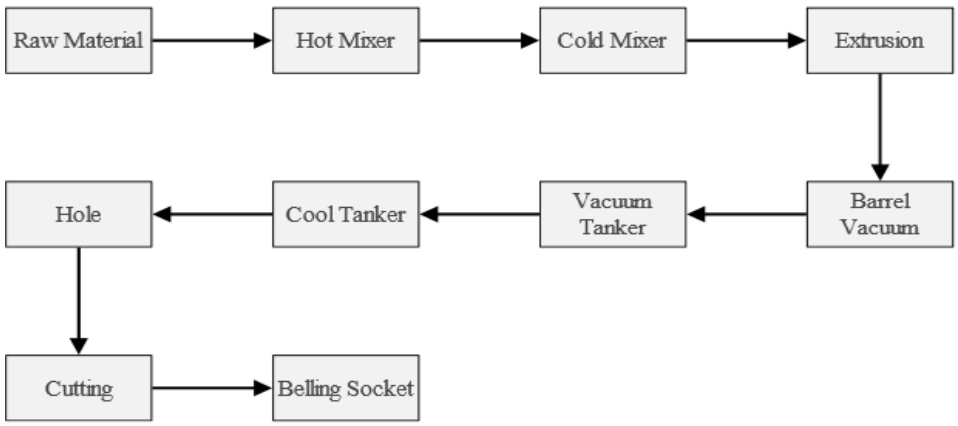


Figure 3 Production Process Map

According to ISO 1452 standards, the process mapping methodology is universally applicable to all PVC-U pipe manufacturing industries. However, the time required for each process stage varies significantly depending on machine capacity and the level of technological implementation. For instance, an automated raw material input system operates considerably faster than a manual input process.

Table 2 presents the time allocation for each production process stage at the case company. These values represent average processing times across different product diameters. Notably, processing times are diameter-dependent. For example, the barrel vacuum stage requires 1 hour for 400mm diameter pipes compared to just 50 minutes for 160mm diameter pipes.

Table 2 Average Observation Time

No	Activities	Day Average (All Time are in Minute)							
		1	2	3	4	5	6	7	Cumulative Average
1	Raw Material Input	9.58	8.74	10.17	11.00	10.01	10.28	11.00	10.11
2	Hot Mixer	18.34	17.02	19.06	18.58	18.46	17.06	19.16	18.24
3	Cold Mixer	27.06	23.07	27.15	27.51	27.02	27.01	27.11	26.56
4	Extrusion	21.51	20.01	22.09	22.07	22.02	21.41	22.03	21.59
5	Barrel Vacuum	56.01	50.10	58.08	59.06	58.59	56.27	57.06	56.45
6	Vacuum Tanker	32.04	29.59	33.38	33.46	33.09	31.58	33.05	32.31
7	Cooler Tanker	4.65	3.48	6.35	5.53	5.33	5.07	5.01	5.06
8	Hole	8.02	6.02	9.04	8.85	8.41	8.46	8.13	8.13
9	Cutting	3.44	2.53	4.38	3.50	3.48	3.48	3.57	3.48
10	Beling Socket	6.57	4.33	7.06	6.75	6.73	6.59	6.47	6.36

For this research analysis, we have adopted the average processing time across all product diameters as our baseline measurement. This approach was selected for three key reasons:

1. It accounts for natural variation in production times due to diameter differences.
2. It provides a representative overview of overall process efficiency.
3. It aligns with the seven days of comprehensive production data collected.

The averaging methodology particularly addresses:

- The technological variation between automated and manual processes.
- The diameter-dependent time fluctuations in critical stage like raw material input processes.
- The need for standardized efficiency metrics across the product stage.

This balanced approach enables meaningful analysis while acknowledging the inherent variability in PVC-U pipe manufacturing processes. The seven-day data collection period ensure these averages reflect typical operational conditions rather than exceptional circumstances.

Dependent Variability

In the manufacturing of PVC-U pipes, several dependent variables significantly influence the production process like product diameter, resource utilization, and also product quality. The diameter of the PVC-U pipe directly impacts production time. The Finding observations reveal a clear correlation between pipe diameter and processing duration. The manufacturing line produces pipes ranging from 160mm to 400mm in diameter. The analysis of these standard sizes demonstrates significant time variations, indicating that changes in pipe diameter necessitate adjustments in the production timeline. Generally, larger diameter may require more processing time due to increased material volume or specifically from the raw material to the belling socket (see Figure 3). In the analysis part use the average time of all diameter time consumption (see Table 2).

Resource utilization is another critical dependent variable, directly influencing production costs. This encompasses a broad range of resources, including human resources, machine capacity, and other operational inputs. Efficient resource utilization is paramount for cost optimization. For example, understanding how different pipe diameters affect machine capacity, labor allocation, and material consumption is important for minimizing waste and maximizing profitability to the organization. The study findings suggest that variations in product diameter can lead to different demands on these resources, highlighting the need for dynamic resource allocation strategies.

Finally, product quality serves as a dependent variability that is intrinsically linked to process optimization and time consumption during production. Achieving high product quality requires mindful control over the manufacturing production process. The time spent on various stages of production, such as raw material to belling socket directly impacts the final quality of the PCV-U pipes product (see the process map Figure 3). Derivations of the process parameters, potentially influenced by changes in production diameter, can lead to defects or inconsistencies. Therefore, optimizing the production process to ensure consistent quality, while also managing the time consumed, is a continuous objective.

Independent Variability

Our study investigates the impact of two key independent variables on the PVC-U pipe manufacturing production process: Value Stream Mapping (VSM) and Discrete Event Simulation (DES). These methodologies are employed to identify areas for improvement and predict the outcomes of proposed changes within the production system.

VM for process analysis serves as a primary independent variable, acting as a diagnostic tool to visualize and analyze the current state of the manufacturing production process. By mapping the entire flow of material and information, from raw material to finished product, VSM allows for the systematic identification of waste bottlenecks, and non-value-added activities. This includes pinpointing areas where production time is unnecessarily extended, resources are underutilized, or quality issues arise. The application of VSM provide a comprehensive understanding of the current operational inefficiencies, laying the groundwork for targeted improvements across all dependent variables. Production time related to diameter, resource utilization, and product quality.

DES for performance predication and validation of process improvement and implications is the second independent variable utilized to model predict the behavior of manufacturing production system under various scenarios. Once potential improvements are identified through VSM. DES allows for the virtual testing of these changes without implementing the real-world implementation in the manufacturing production process. This includes simulating the impact of adjustments to production schedules, machine configurations, human resource allocation, or process flow on dependent variables such as production time for different pipe diameters, overall

resource utilization rates, and potential impacts on product quality. DES provides a powerful predicative capacity, enabling informed decision0-making by evaluating the potential benefits and drawbacks of proposed innervations before their physical implementation. This minimizes risks and optimizes the selection of improvement strategies.

4.3.2. Value Stream Mapping Analysis: identification and characterization of process inefficiencies

As visual represented in Figure 4 of the VSM current state analysis, a critical examination of the production system indicates identifiable inefficiencies within three core processes: raw material input, cutting and belling socket. Theses empirical findings directly align with and underpin a primary objective of the present investigation "to analyze the current manual raw material input process, cutting process, and belling socket process to identify areas of inefficiency and waste."

The VSM specially underscores a notable inefficiency within the raw material input process, characterized by an observed 10.11 minutes, 3.48 minutes for cutting and 4.36 minutes for belling socket per batch processing time. This metric, while initially broad, strongly indicates the prevalence of substantial NVA activities embedded within the initial stages of material handling and preparation; such as transport, material handling methods, inefficient transport, or delay attributes to inefficient process standardization or information flow.

To directly address this identified inefficiency and fulfill the stated research objective, the subsequent analytical phase necessitates a meticulous decomposition of all constituent activities within the raw material input process. This involves conducting a comprehensive time study for each micro activity, systematically documenting the duration of every step from the point of material reception and unloading, through internal logistics and storage to preprocessing inspections and ultimate delivery to the mixer. This granular level temporal analysis in indispensable for accurately delineating between VAT and NVAT elements. For instance, while the physical transfer of raw material is intrinsically necessary excessive travel distances or reputative handling cycles would be quantitative classified as NVA. Similarly extended idle times awaiting equipment or personnel re-sorting due to suboptimal initial organization or redundant quality verification steps will be precisely quantified as waste.

By disaggregating the raw material input process into its elementary activities and quantifying their respective time consumptions, this research aims to precisely identify the specific sources and magnitude of waste contributing to the observed 10.11 minutes batch processing time. This empirically derived understanding will then serve as the foundation premise for the development of targeted interventions and process improvements, directly mitigating identified areas of waste and consequently optimizing the overall production flow. this systematic and data driven approach is paramount for translating qualitative VSM observations into actionable impactful strategic recommendations for process enhancement.

The current production process of the case company is visualized through VSM, which illustrates the PVC-U pipe production line and identifies both VA and NVA time.

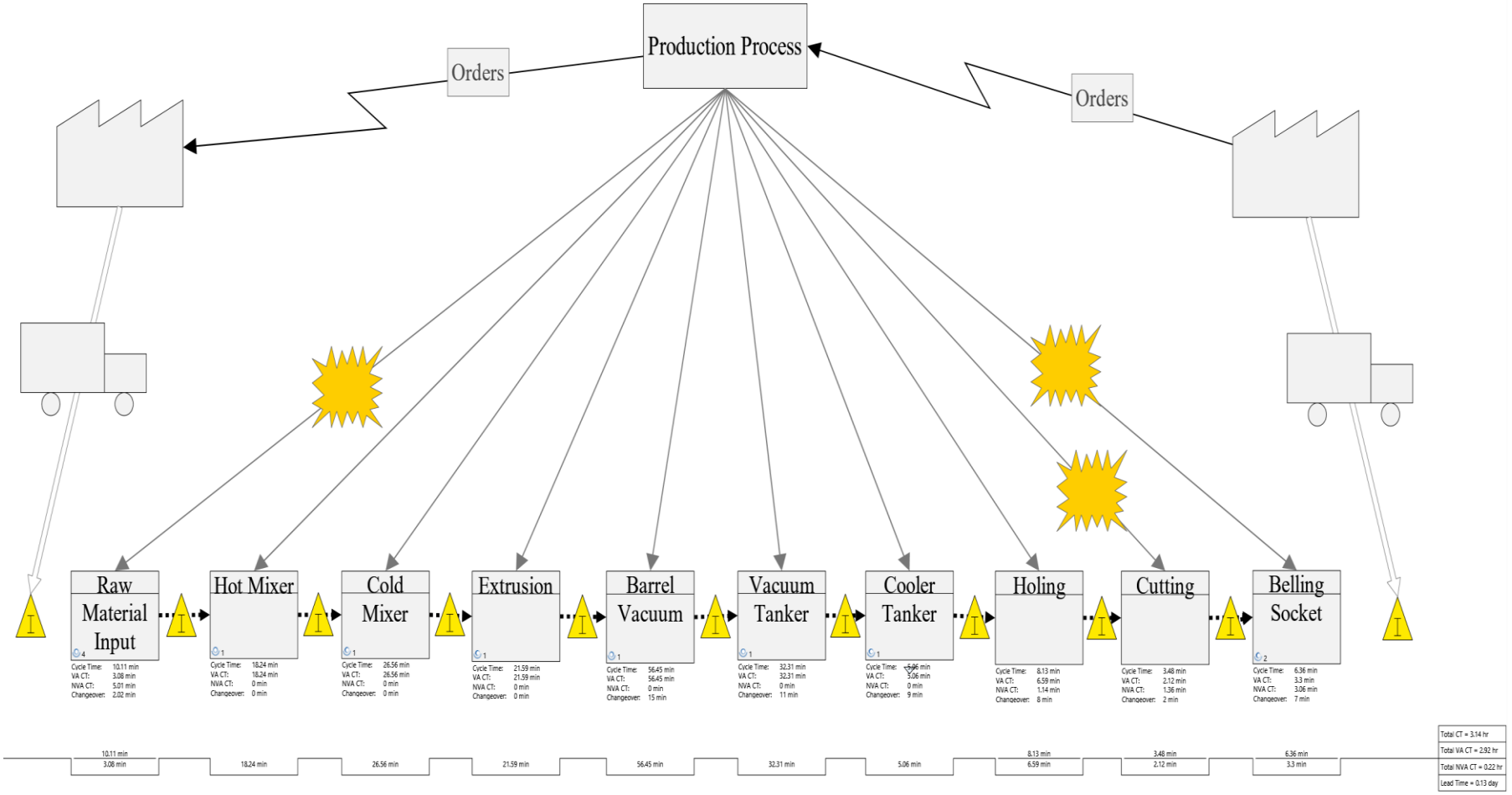


Figure 4 Current Production Process VSM

Table 3 Value-Added and Non-Value-Added Time

No	Process Name	Process Time (All Time are in Minute)			Remark
		Total Process Time	Value-Added Time	Non-Value-Added Time	
1	Raw Material Input	10.11	5.10	5.01	
2	Hot Mixer	18.24	18.24		__
3	Cold Mixer	26.56	26.56		__
4	Extrusion	21.59	21.59		__
5	Barrel Vacuum	56.45	56.45		__
6	Vacuum Tanker	32.31	32.31		__
7	Cooler Tanker	5.06	5.01		__
8	Holing	8.13	6.59	1.14	
9	Cutting	3.48	4.12	1.36	
10	Belling Socket	6.36	3.3	3.06	

The VSM provides a comprehensive visual representation of the current state of the production process, from raw material input to final product delivery that means the belling socket. The analysis specially targets three critical stages: raw material input process, cutting, and belling socket, which have been identified as key areas for potential improvement because of their bottleneck. In the VSM analysis of the current production process revealed a critical bottleneck in the raw material input process. This stage, crucial for the subsequent cutting and bellying socket operations, is plagued by significant inefficiencies.

Using the VSM snapshot (total cycle is 3.14 h / 188.4 min), the process exhibits an accumulated VA time of 2.94 h (176.4 min) and total NVA of 0.22 h (13.2 min). Waiting measured by the VSM is negligible (≈0 min), implying a high VA efficiency of ~93.6%. The three targeted operations, Raw Material Input (Approximately 5 min, NVA), Holing (Approximately 7 min, VA), and Cutting (~4 min, VA) — are individually short, but together they present realistic opportunities for cumulative cycle-time reduction. Modest improvements (Raw Material Input is 50%, Holing is 25%, Cutting is 25%) would reduce the cycle by about 5.3 minutes (to 183.1 min, VA share approximately 94.8%). A more aggressive program could yield is 8.4 minutes savings

(cycle is 180.0 min, VA share is 95.6%). Thus, focused kaizen in these three operations will increase VA efficiency and shave important minutes from the daily throughput, especially when combined with validation under realistic release and variability patterns.

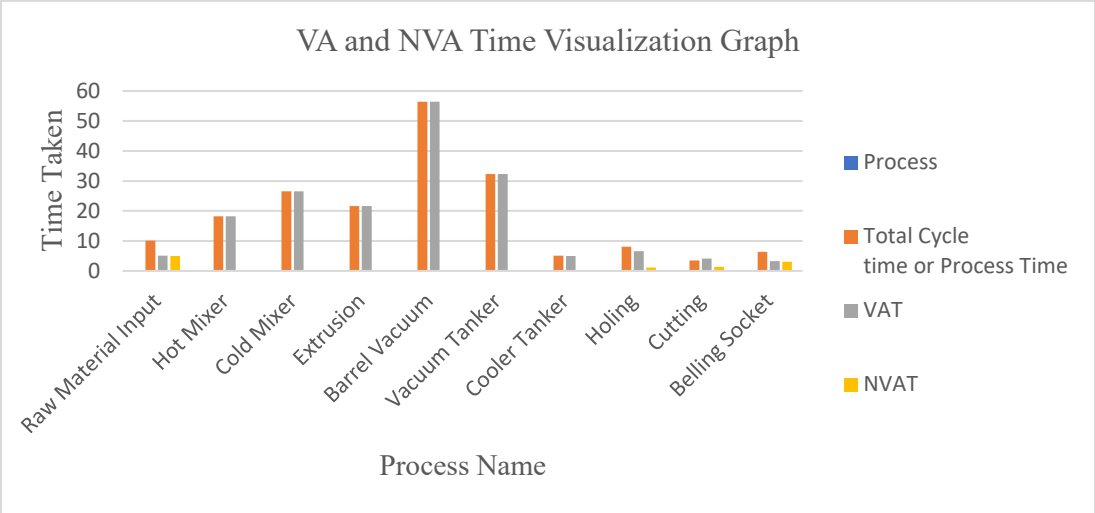


Figure 5 VA and NVA Time Visual representation

1. The VSM showed that the R**aw Material Input Process** consumes a total cycle time of 10.11 minutes. A detailed examination into this duration showed a concerning distribution:
   - VAT: Only 3.06 minutes approximately 30% of the total raw material input production time. This is the time spent on activities that directly transform the raw material, adding value to the product from the customer's perspective.
   - NVAT: 5.01 minutes approximately 50% of the total production process. This time is consumed by activities that do not add value, such as waiting, searching, selecting materials, transport, and or unnecessary movement.

The calculation clearly illustrates is very important and shown below:

$$Total\ Times = 10.11\ munitues$$

$$NVA\ Times = 5.01 minutes$$

$$NVA\ Time\ Percentage = ?$$

$$NVA\ Time\ Percentage = \left(\frac{NVA\ Time}{Total\ Time}\right) * 100\% = \left(\frac{5.01\ minutes}{10.11\ minutes}\right) * 100\%$$

$$= \frac{501\ minutes\ per\ \%}{10.11\ minutes} = \frac{501\%}{10.11} = 49.56\%$$

The means nearly half of the time spent on raw material input process is wasted on activities that do not contribute to product output. This length proportion of NVAT is a significant obstacle to the company overall production process efficiency and directly impacts throughput, lead time, and operational costs.

Impact on production process efficiency

The identified 49% NVA time in the raw material input process has a deep and negative impact on the entire production system:

- Reduce throughput: The extended cycle time for raw material input limits how quickly material can enter the production process line, effectively recording the maximum output of the entire system.
- Increased lead time: Delays at the initial stage of affect through entire process, extending total time it takes for a product to move from raw material to finished.
- High operational costs: Time spent on NVA activities translates directly into wasted labor, energy, and facility utilization. Its time paid for without a corresponding increase in value.
- Potential for bottlenecks: this inefficiency creates a bottleneck at the very beginning of the process, starving subsequent workstations (like cutting and bellying socket) of the necessary material, leading to idle time and further inefficiencies downstream.
- Low productivity: Overall, the high NVA time means that the resources deployed in the raw material input process are not being utilized to their potential, resulting in lower productivity per shift or per employee.

The alarming figure underscores the urgent need for intervention to streamline the raw material input process and eliminate these wasteful activities.

Scenario 1 (Six sub scenarios): A targeted solution for raw material input process:

To address this critical challenge and improve production process efficiency, Scenario 1 has been developed. This proposed solution specially targets the identified issues within the raw material input process, aiming to significantly reduce or eliminate the 49% NVA time.

While the specifics of Scenarios 1 are not detailed here, its core objective is to provide a reliable and sustainable solution for the identified inefficiencies.

- Scenario 1.1. Process optimization re-evaluating and redesigning the workflow to eliminate unnecessary steps, movements, and waiting times.
- Scenario 1.2. Automation introducing automated systems for material handling, sorting, or feeding to reduce manual effort and NVA time.
- Scenario 1.3. Layout improvement reconfiguring the physical layout of the raw material input area to minimize travel distances and improve accessibility.
- Scenario 1.4. Standardization implementing standardizing producers and checklists to ensure consistency and reduce errors and reworks.
- Scenario 1.5. Supplier relation management collaborating with suppliers ensure timely and organized delivery of material, reducing inspection or sorting time upon arrival.
- Scenario 1.6. Training and empowerment provide staff with the necessary training and tools to efficiency manage raw material input, developing a culture of continuous improvement.

By implementing Scenarios 1, a significant reduction in the raw material input process cycle time, leading to a substantial improvement in overall production process efficiency, reduced costs, and increased throughput. This proactive approach will be instrumental in transforming a major bottleneck into a streamlined and VA initial stage of the production process.

2. The VSM showed that the cutting production process consumes a total cycle time of 3.48 minutes. An in-depth examination into this duration showed a concerning distribution:

The VSM revealed that the cutting stage is another significant area of inefficiency within the production process.

$$Total\ Times = 3.48\ munitues$$

$$NVA\ Times = 1.36 minutes$$

$$NVA\ Time\ Percentage = ?$$

$$NVA\ Time\ Percentage = \left(\frac{NVA\ Time}{Total\ Time}\right) * 100\% = \left(\frac{1.36\ minutes}{3.48\ minutes}\right) * 100\%$$

$$= \frac{136\ minutes\ per\ \%}{3.48\ minutes} = \frac{136\%}{3.48} = 39.06\%$$

This indicates that nearly 39% of the cutting process time is wasted on non-value-added activities such as repositioning, unnecessary handling, equipment adjustments, and waiting for material flow.

Impact on production process efficiency

The high NVAT in the cutting stage has several negative implications:

- Reduced efficiency: a short process (3.48 minutes) should ideally be a quick flow step, but the high NVAT significantly reduces its effectiveness.
- Increased lead time: delays in cutting and unnecessary waiting before products can move to the belling socket stage.
- Equipment underutilization: valuable machine time is spent idle or non-essential adjustments rather than productive cutting.
- Operators fatigue and errors: excuses manual handling and repetitive adjustments increase the risk of mistakes and worker strain.
- Flow disruption: as cutting precedes belling, inefficiencies here amplify bottlenecks downstream, further delaying throughput.

Scenario 2: Targeted solution for cutting process

To address the inefficiencies in the cutting process, scenario 2 is proposed. this solution focus on reducing the 39% NVAT and optimize the stage for higher throughput.

- Scenario2.1. Process simplification streamline cutting sequences and eliminate redundant actions.
- Scenario 2.2. Machine adjustment optimization standardizes and pre-set cutting equipment parameters to minimize downtime during material changeovers.
- Scenario 2.3. Workstation layout improvement position tool, materials, and fixtures to reduce unnecessary operator movements.
- Scenario 2.4. Automation and sensor integration use semi-automated or sensor driven cutters to ensure accuracy and reduce manual effort.

By implementing Scenario 2, the cutting stage will experience a reduction in cycle time, fewer disruptions, and mother material flow to the belling socket process. this will minimize waste, improve operator efficiency, and support overall production performance.

3. The VSM showed that the belling socket production process consumes a total cycle time of 6.36 minutes. An in-depth examination into this duration showed a concerning distribution:

The VSM revealed that the belling socket is another significant area of inefficiency within the production process.

$$Total\ Times = 6.36\ munitues$$

$$NVA\ Times = 3.06\ minutes$$

$$NVA\ Time\ Percentage = ?$$

$$NVA\ Time\ Percentage = \left(\frac{NVA\ Time}{Total\ Time}\right) * 100\% = \left(\frac{3.06\ minutes}{6.36\ minutes}\right) * 100\%$$

$$= \frac{306\ minutes\ per\ \%}{6.36\ minutes} = \frac{306\%}{6.36} = 48.11\%$$

This indicates that nearly 48.11% of the belling socket production process time is wasted on non-value-added activities such as repositioning, unnecessary handling, equipment adjustments, and waiting for material flow.

Impact on production process efficiency

The high NVAT in the belling socket production process has several negative impacts:

- Reduced productivity almost half of the time is consumed by NVAA, limiting the efficiency of the final stage.
- Extended Lead Time as the belling socket is the last step before product delivery, inefficiencies here directly delay order completion.
- Increased operational costs labor and machine usage on non-essential activities drive up production costs without adding value.
- Bottleneck amplification delays in belling socket operations create work-in-progress (WIP) buildup, disrupting smooth product flow.
- Quality risks frequently adjustments and handling increase the risk of product defects or inconsistencies.

Scenario 3: Targeted solutions for belling socket production process inefficiencies

To reduce the 48% NVAT in the belling socket stage, Scenario 3 is proposed. This solution focuses on eliminating unnecessary actions and improving machine operator efficiency.

- Scenario 3.1. Workflow optimization streamlines the sequences of belling socket operations to remove redundant repositioning and manual adjustments.
- Scenario 3.2. Machine automation introduced automated or semi-automated belling machine to ensure consistency and reduce manual intervention.
- Scenario 3.3 Fixture and tooling improvement design specialized fixtures to minimize handling and improve precision.
- Scenario 3.4. Layout redesign recognizes the workstation to ensure smoother material flow and reduce unnecessary operator movement.

Implementing Scenario 3 will significantly reduce cycle time, eliminate bottlenecks at the final production stage, and ensure smoother delivery of finished goods. This will lead to higher throughput, reduced costs, and improve overall production system efficiency.

Solution Scenarios Identification

Table 4 presents the solution scenarios developed for the three critical bottlenecks identified in the production process: raw material input, cutting and belling socket. in total, three main scenarios, were formulated, consisting of 13 sub-scenarios targeting specific inefficiencies.

Table 4 Solution Scenarios Identification

No	Solution Scenarios	Scenario Types			Remarks
		Scenario 1	Scenario 2	Scenario 3	
1	Process optimization	√			
2	Automation	√			
3	Layout improvement	√			
4	Standardization	√			
5	Supplier relation management	√			
6	Training and empowerment	√			
7	Process simplification		√		
8	Machine adjustment optimization		√		

9	Workstation layout improvement	√	
10	Workflow optimization	√	
11	Machine automation		√
12	Fixture and tooling improvement design		√
13	Layout redesign		√

Interpretation and analysis

From the table, it is evident that although 13 sub-scenarios were identified across the three main scenarios, several of them share common improvement themes. For example:

- Process optimization, workflow optimization, and process simplification all address the removal of redundant steps and unnecessary activities in different stages of production.
- Layout improvement, workstation layout improvement, and layout redesign are closely related, focusing on reducing waste by reconfiguring the physical arrangement of machines, tools, and materials.
- Automation and machine automation hare the same principle of reducing manual intervention by introducing mechanized or semi-automated solutions.

This repetition across different scenarios highlights a set of core improvement strategies that can be applied holistically to multiple bottlenecks.

Prioritization of Sub-Scenarios

When assessing which sub-scenarios are most preferable and achievable in alignment with the research objectives, several factors should be considered: feasibility, cost effectiveness, and ease of implementation.

1. High feasibility and quick wins
    - Process optimization, workflow optimization, process simplification these can be achieved with minimal capital investment through lean management practices and workflow redesign.
    - Training and empowerment capacity building for operators can deliver immediate improvements in consistency and efficiency.

- Standardization implementing checklists, procedures, and standardize work instructions enhance process reliability.

2. Moderate investment, high impact
   - Layout improvement, workstation layout improvement, layout redesign while requiring some physical changes, these deliver significant reductions in movement waste and waiting times.
3. Long Term strategic investments
   - Automation, machine automation fixture and tooling improvement design these options involve higher costs and longer implementation timeline but can provide sustainable efficiency gains and error proofing.
   - Supplier relation management collaboration with supplier requires systematic changes are coordination but can strengthen raw material flow reliability.

While 13 sub-scenarios have been proposed under the three main scenarios, there is considerable thematic overlap particularly in the areas of process optimization layout improvement, and automation. These repeated strategies suggest that the core drivers of efficiency across the production stages are similar in nature. therefore, prioritizing process optimization, layout-related improvement, and standardization provides the most practical and achievable pathway toward the research objectives of enhancing production process efficiency. More capital-intensive interventions such as automation and tooling design may be considered as long-term solutions once foundational investments are secured.

So, the final prioritized scenarios are as follows:

- Scenario 1: Process automation
- Scenario 2: Workflow layout improvement
- Scenario 3: Process optimization

These three scenarios, identified through the VSM analysis, have a high impact on enhancing the company's production process efficiency, improving competitiveness in the market, and strengthening overall operational performance.

4.3.3. Discrete Event Simulation Outcomes

4.3.3.1. Model scope and objective

The scope of DES model developed in this research encompasses the entire production process, beginning from raw material input stage and extending through to the belling

socket stage, which represents the final step before product delivery. the inclusion of all ten sequential processes ensure that the model accurately mirrors the actual production flow and captures the interdependencies between stages. By replicating the observed system, the simulation provides a controlled environment in which to analyze inefficiencies, assess improvement strategies, and support data-driven decision-making.

The primary objective of the model is to examine how production process efficiency can be enhanced through targeted improvement scenarios identified in the VSM analysis. Specifically, the simulation evaluates the impact of reducing NVA time in three critical bottleneck stages: raw material input, cutting, and belling socket. these processes were prioritized evacuate of their high production of NVA activities and their significant contribution to overall system delays.

To achieve this objective, the model incorporates entities (representing production batches or units), resources (corresponding to machine, mixers, and workstation), and workflows (defining the sequential routing of entities through the system). By applying stochastic processing times based on Gamma probability distributions derived from real world time study data, the model accounts for validity in operations. the DE framework allows for experimentation with both baseline and improved scenarios, enabling comparative analysis of the throughput, lead time, resource utilization, and WIP. Ultimately, the model serves as a decision-support tool, guiding managers toward the most feasible and impactful strategies for improving efficiency, reducing waste, and increasing production capacity.

4.3.3.2. Processing-time inputs (baseline)

The DES model requires the specification of processing times at each stage of the production system. To ensure realism, them these inputs were delivered directly from the seven-day time study data collected for all ten processes, ranging from raw material input to the belling socket operation. This empirical dataset provided the minimum, maximum, and mean cycle times for each process, which formed the basis for the probability distributions used in the model.

Given the nature of available data, a Gamma probability distribution was selected to represent processing times. The gamma probability distribution is widely applied in manufacturing system simulation studies when data is limited but bounded, as it allows

for explicit definition of the Alpha and Beta values. In this case, the observed minimum time was used as the distribution's lower bound, the average (mean) time was taken as and the standard deviation.

This approach ensured that the stochastic variability of real operations was reflected in the model while maintaining consistency with the actual observations.

For Example, the Raw Material Input process was modeled with Gamma distribution of:

$$GAMMA(BETA, ALPHA)$$

$$GAMMA(0.053\ , 189.634)\ for\ Raw\ Material\ Input\ process$$

Based on observed variation across the seven days. similarly, major processes such as the Hot Mixer and Barrel Vacuum were represented as:

$$GAMMA\ (0.036\ , 507.687)\ for\ Hot\ Mixer\ process$$

$$GAMMA(0.139\ , 405.78)\ for\ Barrel\ Vacuum\ process$$

$$GAMMA(50.01, 56.45, 59.06)\ for\ Barrel\ Vacuum\ process\ respectively.$$

Shorter tasks, such as cutting and belling socket, were model as:

$$GAMMA\ (0.071\ , 49.199)\ for\ Cutting\ process$$

$$GAMMA\ (0.113\ , 56.267\ )\ for\ Belling\ Socket\ process.$$

The complete set of baseline distributions Table 5 provides the model with realistic variability and allows the system to generate reliable performance estimates under current operating conditions. Importantly, these baseline distributions also serve as the reference point for evaluating improvement scenarios, where modifications to the mean times of selected bottleneck processes (Raw Material Input, Cutting, and Belling Socket) are tested against this benchmark.

Table 5 DES input distributions baseline

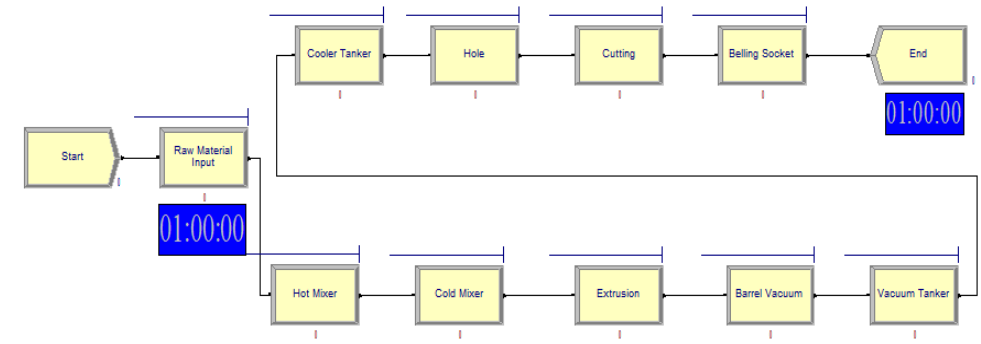
No	Process	Suggested Dist. (Gamma)		Capacity (units/hour)
		Alpha	Beta	
1	Raw Material Input	189.635	0.0533	5.93

2	Hot Mixer	507.687	0.0359	3.29
3	Cold Mixer	343.325	0.0774	2.26
4	Extrusion	959.007	0.0225	2.78
5	Barrel Vacuum	405.780	0.1391	1.06
6	Vacuum Tanker	629.641	0.0513	1.86
7	Cooler Tanker	38.649	0.1309	11.86
8	Holing	77.166	0.1054	7.38
9	Cutting	49.199	0.0708	17.24
10	Belling Socket	56.267	0.1130	9.43

Using the data presented in Table 5, the DES model was developed to represent the current state of the production system. The Gamma distributions assigned to each process capture the natural variability observed in the time study, ensuring that the simulation mirrors the stochastic nature of real operations. By establishing these baseline inputs, the model provides a reliable platform for testing and comparison.

The next step involved conducting simulation experiments to analyze the performance of the system under both current conditions and proposed improvement scenarios. Specifically, the experiments focused on evaluating the impact of reducing NVA times at the Raw Material Input, Cutting, Belling Socket processes identified as critical bottlenecks in the VSM analysis. These scenarios allowed the study to assess how targeted interventions could influence key performance indicators such as throughput, lead time, resource utilization, and WIP levels.

In this way, the DES model serves as a decision-support tool, enabling systematic evaluation of improvement strategies before actual implementation. The experiments provide quantitative evidence of how process efficiency can be enhanced, thereby offering practical insights to the case company in its pursuit of reduced waste, shorter cycle times, and higher overall productivity. The following section presents the simulation results and discusses their implications for the production system.



Process - Basic Process

	Name	Type	Action	Priority	Resources	Delay Type	Units	Allocation	Expression	Report Statistics
1	Raw Material Input	Standard	Seize Delay Release	High(1)	6 rows	Expression	Minutes	Wait	GAMM(0.053 , 189.635)	☑
2	Hot Mixer	Standard	Seize Delay Release	High(1)	6 rows	Expression	Minutes	Value Added	GAMM(0.036 , 507.687)	☑
3	Cold Mixer	Standard	Seize Delay Release	High(1)	1 rows	Expression	Minutes	Value Added	GAMM(0.077 , 343.325)	☑
4	Extrusion	Standard	Seize Delay Release	High(1)	1 rows	Expression	Minutes	Value Added	GAMM(0.023 , 959.007)	☑
5	Barrel Vacuum	Standard	Seize Delay Release	High(1)	1 rows	Expression	Minutes	Value Added	GAMM(0.139 , 405.78)	☑
6	Vacuum Tanker	Standard	Seize Delay Release	High(1)	1 rows	Expression	Minutes	Value Added	GAMM(0.051 , 629.649)	☑
7	Cooler Tanker	Standard	Seize Delay Release	High(1)	1 rows	Expression	Minutes	Value Added	GAMM(0.131 , 38.649)	☑
8	Hole	Standard	Seize Delay Release	High(1)	1 rows	Expression	Minutes	Value Added	GAMM(0.105 , 77.166)	☑
9	Cutting	Standard	Seize Delay Release	High(1)	1 rows	Expression	Minutes	Wait	GAMM(0.071 , 49.199)	☑
10	Belling Socket	Standard	Seize Delay Release	High(1)	1 rows	Expression	Minutes	Wait	GAMM(0.113 , 56.267)	☑

Figure 6 Process model and analysis

The DES results highlight that the current production system is constrained by a small number of processes that contribute disproportionately to inefficiency. The raw material input process demonstrated the highest utilization 93%, making it as a primarily bottleneck, while the Cutting and Belling Socket processes introduced delays through NVA. WIP build up average 5.6 entities were concentrated upstream, particularly before the mixers. The outcomes confirm the inefficiencies identified through VSM and underscore the importance of targeted improvements. However, the overall throughput remains constrained by the long cycle time of the barrel vacuum process, indicating that addressing this stage is essential to achieve the company's production target of 4 tons per 8 hours, while the current production process capacity is only 3 ton per 8 hours.

4.3.3.3. Model Logic (pseudo-algorithm and aligned to your VSM scenarios)

The development of the DES model followed a structured logic design to replicate the actual production flow from Raw Material input through to the Belling Socket. Each entity in the model represents a production batch, moving sequentially through all ten processes defined in Table 4. The following pseudo-algorithm summarizes the model logic:

- Entity Creation: at the Raw Material Input stage, representing incoming production batches. Arrival pattern configured to ensure continuous material availability for processing
- Routing through processes: Entities are routed sequentially through Raw Material to Belling Socket. Each process is modeled using a Gamma distribution (minimum, mean, maximum) derived from the time study (Table 4).
- Resource Seizing and Delays; At each stage, the entity sizes the relevant machine resource. Processing time is draw from the specified Gamma distribution. After completion, the resource is released, and the entity moves to the next stage.
- Queueing and Variability; If the resource is busy, entities wait in a first-come, first-served (FCFS) queue. Queue lengths and waiting times vary based on station capacity and processing time variability.
- Entity Exit; After completion of the Belling Socket process, entities leave the system, making the production of a finished product.

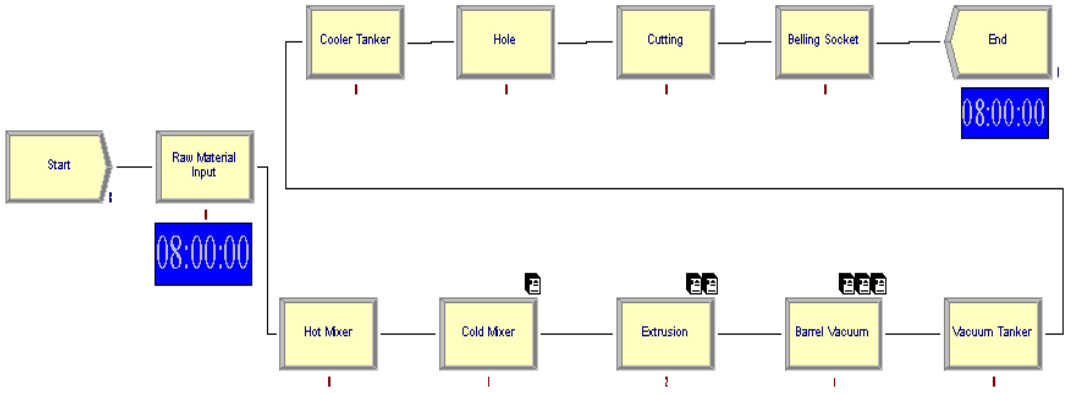


Figure 7 Process Model

4.3.3.4. Reporting and interpretation

The reporting of the DES model focused on quantifying key performance indicators (KPIs) such as VA time, NVA time, waiting time, resource utilization, and WIP. These measures provide insight into how the system performs under the baseline configuration and where inefficiencies persist.

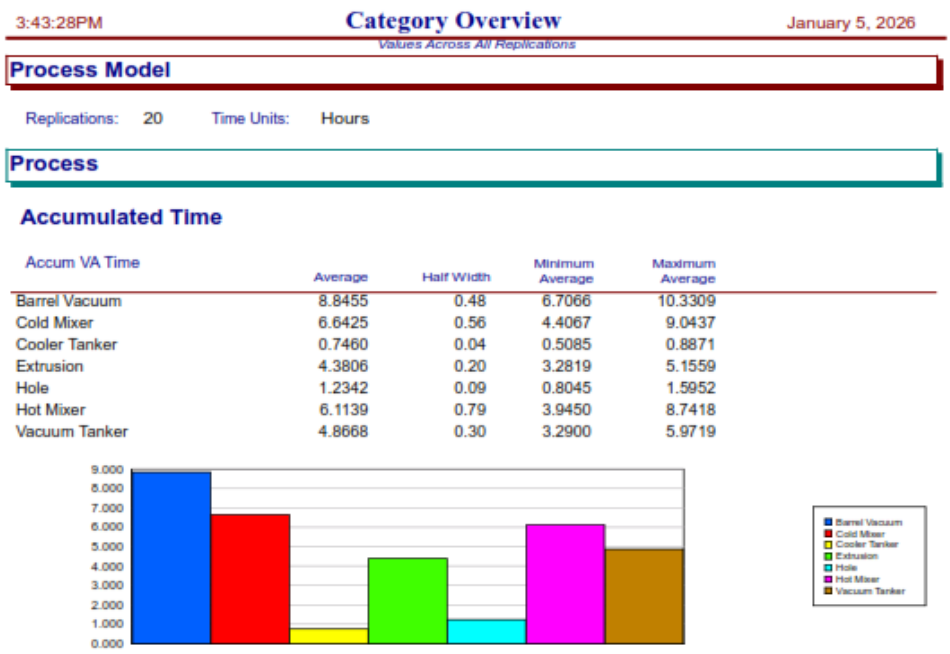
The accumulated VA time profile provide a in Figure 4 and 8 of how value is progressively added to the product as it advances through the production line. At the initial stage, Raw Material Input contributes only 5 minutes, reflecting its preparatory

role with minimal direct transformation. The Hot Mixer increases the accumulated VA to 23 minutes, followed by the Colder Mixer, which raises it further to 49 minutes. These stages are important for material blending and conditioning, representing essential preparatory transformations before shaping.

A significant increase occurs during the Extrusion stage, which elevates the accumulated VA to 71 minutes. The largest single contribution arises from the Barrel Vacuum, where accumulated VA jumps to 127 minutes. This confirms the Barrel Vacuum as the most time-consuming and value-intensive stage, acting as the primary bottleneck that governs system throughput.

Subsequent processes contribute more moderately. The Vacuum Tanker increases the accumulated VA to 160 minutes, the Cooler Tanker to 165 minutes, and Holing to 172 minutes. These stages play an important role in stabilizing the product and ensuring dimensional accuracy, though their contributions to total VA are smaller.

The final finishing operations Cutting and Belling Socket raise the accumulated VA to 176 minutes and 181 minutes, respectively. Their contributions, though relatively small compared to upstream stages, are crucial for meeting customer requirements and final product usability.


3:43:28PM Category Overview January 5, 2026

Values Across All Replications

Process Model

Replications: 20 Time Units: Hours

Process

Accumulated Time

Accum VA Time	Average	Half Width	Minimum Average	Maximum Average
Barrel Vacuum	8.8455	0.48	6.7066	10.3309
Cold Mixer	6.6425	0.56	4.4067	9.0437
Cooler Tanker	0.7460	0.04	0.5085	0.8871
Extrusion	4.3806	0.20	3.2819	5.1559
Hole	1.2342	0.09	0.8045	1.5952
Hot Mixer	6.1139	0.79	3.9450	8.7418
Vacuum Tanker	4.8668	0.30	3.2900	5.9719

Figure 8 Accumulate VA time

At the Finished Goods stage, the accumulated VA time at 176.5 to 181 minutes, representing the total value-added content of the process. This figure serves as a

benchmark for evaluating process efficiency when compared against the total cycle time. The difference highlights the proportion of non-value-added activities, such as waiting and material handling, that present opportunities for lean improvement.

Overall, the accumulated VA time profile reveals an uneven distribution of value creation, with the Barrel Vacuum emerging as the dominant stage. Optimizing this process offers the greatest potential for throughput improvement, while downstream operations like Cutting and Belling Socket remain essential for quality assurance and customer satisfaction.

The accumulated NVA time see Figure 4 illustrates how NVA activities contribute to the overall cycle time of the production line. At the initial stage, Raw Material Input is the only process that directly adds measurable NVA time, approximately 5.5 minutes. This reflects the manual effort required for weighing, recording, and transporting raw material, which does not directly transform the product. As the product progresses through the line, subsequent processes do not add significant NVA time, and the accumulated NVA stabilizes at around 13 minutes for the entire cycle. Although this value is relatively small compared to the total cycle time of 176.5 minutes, it represents 7% of the process time and highlights opportunities for lean improvements. However, this time is visualized only in three production processes: Raw Material Input, Cutting, and Holing. Reducing or eliminating the NVA at Raw Material Input, through pre-kitting, automation, or digital recording systems, would have a direct impact on efficiency. Even modest reductions would improve the VA/NVA ratio and reduce operator workload without compromising product quality.

The accumulated waiting time profile see Figure 9 shows where delays occur due to queuing and resource unavailability. The largest waiting contribution occurs before the Barrel Vacuum process, which is the system bottleneck. Products often queue at this stage, leading to idle time and increased work-in-progress (WIP).

3:43:28PM **Category Overview** January 5, 2026

Values Across All Replications

Process Model

Replications: 20 Time Units: Hours

Process

Accumulated Time

Accum Wait Time

	Average	Half Width	Minimum Average	Maximum Average
Barrel Vacuum	22.5032	3.68	3.1362	35.3179
Belling Socket	0.9339	0.06	0.5744	1.1382
Cold Mixer	40.9639	10.05	3.7457	89.2931
Cooler Tanker	0.00	0.00	0.00	0.00
Cutting	0.5111	0.03	0.3382	0.6223
Extrusion	31.8785	6.36	2.5874	56.8530
Hole	0.00	0.00	0.00	0.00
Hot Mixer	2.6311	1.16	0.00	11.5954
Raw Material Input	5.5538	1.32	2.1210	10.5542
Vacuum Tanker	0.00	0.00	0.00	0.00

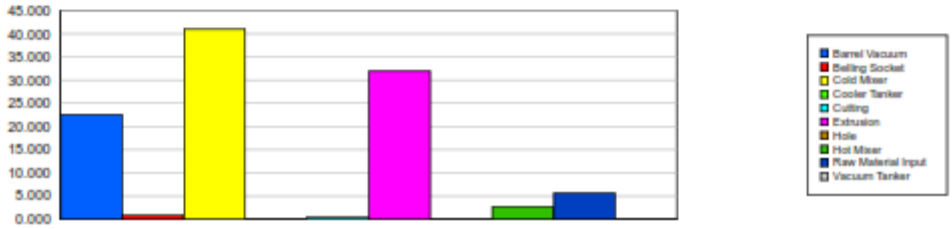


Figure 9 Waiting Time

The results and interpretation of the study provide a comprehensive understanding of the current production process performance. The accumulated time profiles revealed that while the system demonstrates a high proportion of VA activities, significant inefficiencies persist due to NVA operations and waiting times. The Barrel Vacuum process emerged as the dominant bottleneck, contributing the largest share of accumulated VA time but also generating the greatest amount of waiting and WIP.

The analysis further highlighted that Raw Material Input remains the primary source of measurable VA time, reflecting manual handling, measurement, and recording activities. Although comparatively small in duration, this step presents a clear opportunity for lean improvements through automation, pre-kitting, or standardization. Similarly, Cutting and Holing were identified as relatively short operations with modest contributions to accumulated VA, yet their efficiency directly affects final product quality and throughput consistency.

Overall, the combined results from VSM and simulation confirm that addressing both localized inefficiencies (such as the Raw Material Input, Cutting, and Holing) and systemic constraints (particularly the Barrel Vacuum) is essential for improving process

efficiency. Optimizing these stages would reduce cycle time, minimize NVA and waiting activities, and improve throughput toward meeting the company's production target.

4.3.4. Integration of VSM and DES

The integration of VSM and DES provides a complementary approach to analyzing and improving complex production systems. While VSM offers a static and visual representation of the current state, DES extends this analysis by capturing system dynamics, variability, and queuing behavior. Combining these tools strengthens the reliability of the analysis and supports the design of more effective process improvement strategies.

VSM alone is effective in identifying VA and NVA activities, mapping process flows, and visualizing material and information linkages. However, it does not account for the stochastic behavior of manufacturing systems, such as machine breakdowns, variable processing times, or batch arrivals. DES addresses these limitations by simulating real-world variability and quantifying performance measures, including throughput, lead time, utilization, and WIP.

By integrating both tools, VSM provides the baseline data for building the DES model, while DES validates and tests the proposed improvements identified through VSM. This synergy ensures that improvement opportunities are both theoretically sound (via VSM) and practically feasible (via DES).

- VSM was developed to capture process times, cycle times, and VA/NVA classifications for each stage of the production process.
- Key performance indicators such as total cycle time (3.14 hours), accumulated VA time (2.94 hours), and NVA time (0.22 hours) were derived from the VSM analysis.
- The VSM results were translated into a process flow diagram and coded into the simulation model.
- Processing times, resources, and batch arrival patterns identified in VSM were used as input parameters for the DES environment.
- The DES model was validated against the VSM current-state results to ensure consistency.

Improvement scenarios suggested by the VSM (e.g., reducing Raw Material Input NVA time, optimizing Cutting and Holing, and alleviating Barrel Vacuum bottlenecks) were tested dynamically in DES to evaluate their impact on throughput and lead time.

The integration revealed that VSM correctly identified the major bottleneck at the Barrel Vacuum stage and highlighted inefficiencies in Raw Material Input, Cutting, and Holing. DES confirmed these findings and quantified the effect of improvements. For example, halving Raw Material Input time had only marginal effect on overall throughput, whereas reducing the Barrel Vacuum cycle time significantly increased output. This demonstrates that DES is necessary to validate whether local improvements (as seen in VSM) translate into meaningful system-wide gains. The integration part is below:

- Strategic Insight: VSM provides a high-level lean perspective, while DES offers detailed performance measures under realistic variability.
- Decision Support: Integration enables managers to prioritize improvements based not only on theoretical value-added ratios but also on dynamic performance outcomes.
- Continuous Improvement: The combined use of VSM and DES supports iterative improvement cycles, where proposed changes are first visualized (VSM), then tested virtually (DES), before being implemented on the shop floor.

Integrating VSM and DES bridges the gap between lean analysis and dynamic system performance. This combined approach ensures that improvement initiatives are both aligned with lean principles and validated through realistic system simulation. For the case company, the integration provided a reliable framework to identify, test, and prioritize process improvements, with particular focus on the Raw Material Input, Cutting, Holing, and Barrel Vacuum processes.

Finally based on the results of the VSM and DES analyses, three priority scenarios were identified for implementation in the case company. These scenarios are expected to deliver the most significant improvements in production efficiency, resource utilization, and competitive performance:

- Process Automation: Automation of manual and repetitive tasks, particularly in the Raw Material Input process, would reduce NVA time, minimize operator

error, and increase process consistency. By eliminating manual measurement and recording, automation directly addresses one of the primary sources of inefficiency and supports lean objectives.

- Workflow Layout Improvement: Redesigning the production layout to minimize material handling, transportation delays, and unnecessary movement will streamline workflow and reduce cycle time. Layout improvement is especially relevant for downstream operations such as Cutting and Holing, where physical repositioning and workpiece transfer currently generate hidden waste.
- Process Optimization: Optimizing critical bottleneck operations most notably the Barrel Vacuum through cycle time reduction, equipment upgrades, or capacity expansion would directly enhance throughput. Process optimization also extends to fine-tuning short but essential stages, such as Cutting and Belling Socket, to ensure quality is achieved without additional delays.

Collectively, these three scenarios are expected to yield high impact by reducing waste, balancing flow, and improving overall production system reliability. Their implementation not only enhances process efficiency but also strengthens the company's competitive advantage in the market by enabling higher productivity, consistent quality, and timely customer delivery.

Table 6 DES input distributions improve

No	Process	Suggested Dist. (Gamma)		Minimum	Mostly	Maximum	Mean	SD	Mean^2	SD^2
		Alpha	Beta							
1	Raw Material Input	233.66	0.022	4.74	5.03	5.4	5.057	0.331	25.570	0.109
2	Hot Mixer	226.05	0.071	15.02	16.24	17.16	16.140	1.073	260.500	1.152
3	Cold Mixer	392.93	0.062	23.07	24.56	25.51	24.380	1.230	594.384	1.513
4	Extrusion	313.70	0.061	18.01	19.59	20.09	19.230	1.086	369.793	1.179
5	Barrel Vacuum	411.17	0.102	40.01	42.06	44.16	42.077	2.075	1770.446	4.306
6	Vacuum Tanker	224.64	0.133	27.59	30.31	31.46	29.787	1.987	887.246	3.950
7	Cooler Tanker	11.92	0.416	3.48	5.06	6.35	4.963	1.437	24.635	2.066
8	Holing	97.69	0.058	5.02	5.99	6.04	5.683	0.575	32.300	0.331
9	Cutting	21.39	0.094	1.53	2.1	2.38	2.003	0.433	4.013	0.188
10	Belling Socket	105.86	0.037	3.53	4.11	4.26	3.967	0.386	15.734	0.149

In the improvement scenarios, particular emphasis was placed on the Raw Material Input process, Holing, Cutting, and Belling Socket. These processes are predominantly manual in nature, making them prone to variability, delays, and waste. As identified through the VSM analysis, they contribute significantly to NVA time and hidden bottlenecks within the production flow. The DES results further validated these findings by dynamically quantifying their impact on overall system throughput and cycle time. Just see the Raw Material Input Process Time taken before and after improvement.

$$Total\ Times\ before\ improvement = 10.11\ munitues$$

$$Total\ Time\ After\ Improvement = 5.01 minutes$$

$$Difference\ Percentage = ?$$

$$Difference\ Percentage = \frac{Total\ Times\ before\ improvement = 100\%}{Total\ Time\ After\ Improvement = ?}$$

$$= \frac{10.11 = 100\%}{6.01 = ?} = \frac{601}{10.11} = 59.45\%$$

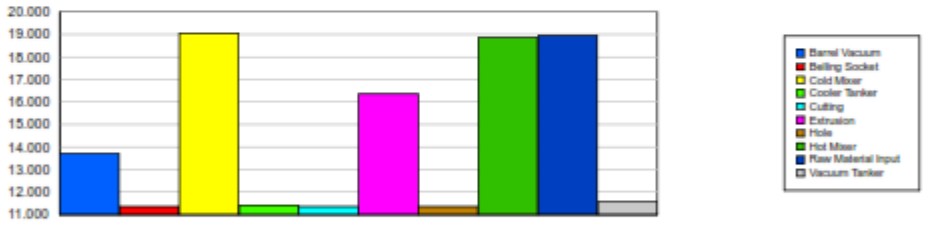
By implementing the proposed improvement measures such as automation for Raw Material Input and SMED-based optimization for Holing, Cutting, and Belling Socket the company can substantially reduce waste and minimize financial losses associated with inefficiency. For instance, in the Raw Material Input process, the mean processing time prior to improvement was 10.11 minutes. After implementing automation, this was reduced by approximately 59.44%, demonstrating a significant efficiency gain. Similarly, improvements in Holing, Cutting, and Belling Socket reduce manual handling delays and improve flow balance across downstream operations.

Replications: 20 Time Units: Hours

Process

Other

Number In	Average	Half Width	Minimum Average	Maximum Average
Barrel Vacuum	13.7000	0.76	9.0000	16.0000
Belling Socket	11.3500	0.57	9.0000	14.0000
Cold Mixer	19.0500	2.11	9.0000	30.0000
Cooler Tanker	11.4000	0.58	9.0000	14.0000
Cutting	11.3500	0.57	9.0000	14.0000
Extrusion	16.3500	1.34	8.0000	21.0000
Hole	11.3500	0.57	9.0000	14.0000
Hot Mixer	18.8500	1.98	9.0000	28.0000
Raw Material Input	18.9500	2.18	9.0000	30.0000
Vacuum Tanker	11.5500	0.58	9.0000	13.0000



Number Out	Average	Half Width	Minimum Average	Maximum Average
Barrel Vacuum	11.5500	0.58	9.0000	13.0000
Belling Socket	11.3500	0.57	9.0000	14.0000
Cold Mixer	16.3500	1.34	8.0000	21.0000
Cooler Tanker	11.3500	0.57	9.0000	14.0000
Cutting	11.3500	0.57	9.0000	14.0000
Extrusion	13.7000	0.76	9.0000	16.0000
Hole	11.3500	0.57	9.0000	14.0000
Hot Mixer	19.0500	2.11	9.0000	30.0000
Raw Material Input	18.8500	1.98	9.0000	28.0000
Vacuum Tanker	11.4000	0.58	9.0000	14.0000

Figure 10 Improved Process Model Output

Overall, the integration of VSM and DES confirmed that focusing on these manual processes not only reduces NVA time but also enhances production system reliability, thereby supporting the company's ability to achieve its throughput targets and strengthen competitiveness in the market.

For comparison, the current process model demonstrates an output of 3 tons per 8-hour shift, which corresponds to approximately 9 tons per day when operating three shifts. In contrast, the improved process model, developed through the integration of VSM and DES, achieves an output of 3.67 tons per 8-hour shift, equivalent to 11 tons per day under the same operating conditions. This represents a substantial performance improvement.

The relative capacity increase can be expressed as:

$$Improvement\ ercentage$$

$$= \frac{Improved\ Process\ Model\ Output - Cureent\ Process\ Model\ Output}{Cureent\ Process\ Model\ Output} * 100\%$$

$$= \frac{11 - 9}{9} * 100\% = \frac{2}{9} = \mathbf{22.22\%}$$

Thus, the improved process model increases system capacity by **22.22%** compared to the baseline scenario. This improvement is primarily attributed to the targeted interventions identified through VSM such as reducing non-value-adding time in Raw Material Input, Holing, Cutting, and Belling Socket and validated through DES, which dynamically quantified their positive impact on throughput. The findings highlight how the combined application of VSM and DES provides both a diagnostic and predictive framework, enabling the case company to move closer to its production target while simultaneously improving resource utilization and overall efficiency.

4.4. Discussion

4.4.1. Validation Against Literature

The findings of this study align closely with evidence reported in the wider literature on lean manufacturing and simulation-based process improvement. Prior studies have emphasized that VSM provides an effective means of identifying VA and NVA activities, but it is limited in its ability to account for system variability and queuing behavior (Al-Rifai, 2024; Lian & Van Landeghem, 2007; McDonald et al., 2002).

The integration of VSM with DES in this research validates these claims by demonstrating that DES complements VSM through its ability to model stochastic behavior, resource utilization, and waiting times. The results confirm findings from previous simulation-based lean studies (Abdulmalek & Rajgopal, 2007; Gurumurthy & Kodali, 2011), which show that improvements suggested by VSM must be tested dynamically before implementation to ensure system-wide feasibility.

Specifically, this study confirmed the dominance of the Barrel Vacuum stage as the system bottleneck a result consistent with the theory of constraints, which has been widely documented in manufacturing research. Similarly, the modest improvement potential in Raw Material Input, Cutting, and Holing reflects previous lean case studies, where localized improvements yield limited throughput benefits if bottlenecks are left unaddressed. In this way, the results of this research are validated by and contribute to the broader body of literature on lean simulation integration.

4.4.2. Practical Implications

The integration of VSM and DES in this study has several important implications for the case company as well as for similar manufacturing environments:

1. Bottleneck Management:

The Barrel Vacuum process was confirmed as the critical system constraint. Efforts to reduce cycle time, parallelize equipment, or enhance capacity at this stage will yield the greatest impact on overall throughput.

2. Targeted Lean Improvements:

Although relatively small in duration, the Raw Material Input process represents a clear NVA activity and should be prioritized for elimination through automation, pre-kitting, or digital recording systems. Cutting and Holing, while VA operations, can be optimized for cycle time without affecting product quality, thereby contributing incremental efficiency gains.

3. Balanced Decision-Making:

Relying solely on VSM may overestimate the benefits of localized improvements. By testing them dynamically in DES, managers can avoid misallocated resources and focus investments on changes that deliver measurable system-wide benefits.

4. Strategic Roadmap for Improvement:

The combined methodology provides a structured roadmap: first identify VA/NVA using VSM, then simulate improvement scenarios in DES, and finally implement validated solutions on the shop floor. This reduces risk, supports evidence-based decisions, and increases the likelihood of sustainable process improvement.

5. Scalability and Transferability

The approach used in this study is transferable to other departments or production lines within the organization, as well as to other firms in the manufacturing sector facing similar bottleneck-driven inefficiencies.

For the case company, practical implementation of the prioritized scenarios requires both technical solutions and organizational commitment:

1. Process Automation

Implementation of automation in the Raw Material Input process should begin with the introduction of electronic weighing, digital recording systems, and semi-automated feeders. These technologies will eliminate manual measurement errors and reduce non-value-added time. The company may adopt a phased approach, starting with pilot testing of automation in one production line before scaling across the facility. Training operators on the new system will ensure smooth adoption and reduce resistance to change.

2. Workflow Layout Improvement

The implementation of layout improvement can be guided by lean tools such as 5S and Systematic Layout Planning (SLP). These tools will help redesign material flow to minimize unnecessary movement and handling. Priority should be given to high-frequency operations such as Raw Material Input, Cutting, and Holing process, where part repositioning currently generates hidden waste. A revised layout should be simulated virtually in DES to test its effectiveness before physical rearrangement, thereby reducing implementation risks and costs.

3. Process Optimization

Optimize the Barrel Vacuum bottleneck through preventive maintenance, cycle-time monitoring, and process standardization in the short term. Long-term strategies may include equipment upgrades or parallel capacity expansion. Cutting and Belling Socket can also be improved with Kaizen events, quick-change tooling, and standardization.

To ensure sustainability, the company should adopt a continuous improvement framework such as Plan–Do–Check–Act (PDCA) or Kaizen. VSM can be revisited periodically to reassess value and waste, while DES can be used to test new scenarios before execution. Together, these tools create a feedback loop between strategy and practice, ensuring that improvements translate into measurable gains.

Chapter Five

5. Conclusion and Recommendations

5.1. Conclusion

This study set out to enhance production process efficiency at the ECWC-GIW by integrating VSM and DES. The integration of these methodologies provided both a diagnostic and predictive framework for analyzing the production system, identifying bottlenecks, and validating improvement scenarios. The results demonstrated the complementary strengths of the two tools: VSM enabled the visualization of VA and NVA activities, while DES dynamically evaluated the system's behavior under realistic operating conditions.

The findings revealed that the Barrel Vacuum process constitutes the dominant system bottleneck, contributing the largest share of accumulated VA time and constraining overall throughput. Additional inefficiencies were identified in the Raw Material Input, Holing, and Cutting processes, all of which are manually implemented and therefore prone to variability, delays, and waste. Collectively, these processes accounted for a significant proportion of cycle time imbalance and hidden non-value-adding activities. By addressing these areas, the company stands to achieve substantial improvements in productivity and resource utilization.

The improvement scenarios tested in DES confirmed the potential of targeted interventions. Automation of the Raw Material Input process was shown to reduce its mean processing time by nearly 60%, directly eliminating manual handling delays. Similarly, the application of quick-changeover and workflow optimization principles to Holing, Cutting, and Belling Socket processes yielded measurable reductions in cycle time and enhanced process balance. At the system level, these improvements increased throughput from 9 tons to 11 tons per day, representing a 22.22% increase in production capacity.

Beyond the specific findings for the case company, this study contributes to the broader literature by demonstrating the practical value of integrating VSM and DES in a developing economy manufacturing context. The research confirmed that while VSM provides a clear baseline for identifying inefficiencies, DES is indispensable for testing the dynamic feasibility of improvement scenarios before physical implementation. This

integrated approach therefore reduces the risk of misallocated resources and supports evidence-based decision-making.

In conclusion, the integration of VSM and DES has proven effective in diagnosing inefficiencies, validating potential improvements, and quantifying their system-wide impact. For ECWC-GIW, the results highlight a clear roadmap for process optimization, focusing on automation, workflow redesign, and bottleneck management. More broadly, the study demonstrates how lean-simulation integration can serve as a structured methodology for achieving sustainable production efficiency improvements in similar manufacturing environments.

5.2. Recommendations

For case company

The results of this study indicate several priority areas for improvement within the pipe production process of ECWC-GIW's. First, the Raw Material Input process should be automated through the introduction of electronic weighing, digital recording, and semi-automated feeding systems. Since this process was identified as a major contributor to NVA time, automation would directly eliminate manual handling delays and improve data accuracy, thereby reducing variability and waste.

Second, the Cutting, Holing, and Belling Socket processes, which are currently manual, should be optimized through the application of lean tools such as Single Minute Exchange of Die (SMED) and standardized work methods. These measures would reduce setup and cycle times, enhance process stability, and ensure consistent product quality.

Third, the workflow layout should be redesigned to minimize unnecessary material movement and handling. Tools such as Spaghetti Diagrams, 5S, and Systematic Layout Planning (SLP) can guide layout changes to improve flow balance. As DES has demonstrated, even modest reductions in handling and transfer times can yield significant improvements in throughput.

Finally, the company should establish a continuous improvement framework, such as Plan–Do–Check–Act (PDCA) or Kaizen, to ensure sustainability of the improvements. Periodically revisiting the VSM and testing scenarios through DES will help the organization track progress, validate future changes, and maintain competitiveness.

For future work

While this study has demonstrated the effectiveness of integrating VSM and DES, several opportunities exist for future research. First, the application of Single Minute Exchange of Die (SMED) should be explored more deeply to minimize setup times in processes such as Cutting and Belling Socket, thereby further increasing system flexibility and throughput.

Second, future studies could incorporate stochastic DES models that capture variability in demand, machine breakdowns, and quality defects. This would provide a more robust analysis of system performance under uncertainty and offer additional insights for decision-making.

Third, the integration of cost-benefit and energy consumption analyses with VSM–DES would enable organizations to balance operational efficiency with financial and environmental sustainability. This would be particularly relevant for firms in developing economies seeking to align competitiveness with sustainability goals.

Fourth, conducting multi-case comparative studies across different manufacturing firms or industries would strengthen the generalizability of the findings and validate the transferability of the methodology.

Finally, the adoption of Industry 4.0 technologies such as IoT-based monitoring, real-time analytics, and digital twins could be integrated into VSM and DES frameworks. Such digital lean systems would enable dynamic decision-making, predictive maintenance, and real-time optimization, further enhancing both efficiency and responsiveness.

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Annex

1. Observation Data

Day 1

Addis Ababa University
College of Technology and Built Environment (CTBE)
School of Mechanical and Industrial Engineering

My name is Ephrem. I completed an MSc in Industrial Engineering and am working on my thesis to partially fulfill the requirements for the Master of Science degree in Industrial Engineering at the College of Technology and Built Environment, Addis Ababa University. This form is used to collect data through observational methods for my thesis, Enhancing Production Process Efficiency through Value Stream Mapping and Discrete Event Simulation: A Case Study of ECWC-GIW.

No	Activities	Batch No					
		1	2	3	4	5	Average
1	Raw Material Input	9.01	8.56	9.21	10.11	11.01	9.58
2	Hot Mixer	18.08	17.59	18.58	19.01	18.44	18.34
3	Cold Mixer	27.08	26.59	27.19	27.19	27.23	27.06
4	Extrusion	22.09	21.38	21.36	21.29	21.41	21.51
5	Barrel Vacuum	56.09	56.59	55.57	55.58	56.21	56.01
6	Vacuum Tanker	32.01	31.15	33.01	32.44	31.59	32.04
7	Cooler Tanker	5.01	4.59	4.56	4.58	4.49	4.65
8	Hole	8.12	8.12	7.59	8.11	8.15	8.02
9	Cutting	3.35	3.45	3.5	3.4	3.48	3.44
10	Beling Socket	6.5	6.38	6.42	6.55	7.01	6.57

Day 2

Addis Ababa University
College of Technology and Built Environment (CTBE)
School of Mechanical and Industrial Engineering

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No	Activities	Batch No					
		1	2	3	4	5	Average
1	Raw Material Input	8.58	8.55	9.01	9.03	8.55	8.74

2	Hot Mixer	17.11	16.45	17.08	17.01	17.44	17.02
3	Cold Mixer	23.02	23.05	23.13	23.57	22.59	23.07
4	Extrusion	20.19	19.44	20.21	20.12	20.09	20.01
5	Barrel Vacuum	51.06	50.4	49.58	49.29	50.16	50.10
6	Vacuum Tanker	29.11	29.15	30.02	30.24	29.45	29.59
7	Cooler Tanker	3.55	3.49	3.34	3.59	3.43	3.48
8	Hole	6.21	6.02	6.12	5.59	6.15	6.02
9	Cutting	2.56	2.51	2.53	2.48	2.58	2.53
10	Beling Socket	4.15	4.38	4.42	4.47	4.21	4.33

Day 3

Addis Ababa University
College of Technology and Built Environment (CTBE)
School of Mechanical and Industrial Engineering

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No	Activities	Batch No					
		1	2	3	4	5	Average
1	Raw Material Input	9.51	9.45	10.25	11.17	10.45	10.17
2	Hot Mixer	19.08	19.05	19.08	19.01	19.09	19.06
3	Cold Mixer	27.25	27.43	27.03	27.04	27.01	27.15
4	Extrusion	22.15	22.28	22.25	22.29	21.49	22.09
5	Barrel Vacuum	59.08	57.57	57.57	58.05	58.12	58.08
6	Vacuum Tanker	33.41	33.25	33.21	33.44	33.59	33.38
7	Cooler Tanker	6.21	6.43	6.36	6.38	6.39	6.35
8	Hole	9.19	9.12	9.21	8.59	9.09	9.04
9	Cutting	4.25	4.45	4.34	4.41	4.47	4.38
10	Beling Socket	7.05	7.03	7.12	7.09	7.01	7.06

Day 4

Addis Ababa University
College of Technology and Built Environment (CTBE)
School of Mechanical and Industrial Engineering

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No	Activities	Batch No					
		1	2	3	4	5	Average
1	Raw Material Input	11.5	11.2	9.9	11.8	10.6	11.00
2	Hot Mixer	18.46	18.48	18.53	18.41	19.02	18.58
3	Cold Mixer	27.45	27.44	28.18	27.41	27.08	27.51
4	Extrusion	21.49	22.38	21.56	22.44	22.49	22.07
5	Barrel Vacuum	59.07	59.08	59.04	59.09	59.02	59.06
6	Vacuum Tanker	33.02	34.09	34.08	33.04	33.09	33.46
7	Cooler Tanker	5.51	5.59	5.56	5.53	5.46	5.53
8	Hole	8.53	8.54	9.09	9.02	9.05	8.85
9	Cutting	3.49	3.5	3.54	3.48	3.47	3.50
10	Beling Socket	6.59	6.57	7.01	6.58	7.02	6.75

Day 5

Addis Ababa University
College of Technology and Built Environment (CTBE)
School of Mechanical and Industrial Engineering

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No	Activities	Batch No					
		1	2	3	4	5	Average
1	Raw Material Input	9.04	10.2	9.01	11.4	10.4	10.01
2	Hot Mixer	18.38	18.39	18.47	18.51	18.54	18.46
3	Cold Mixer	27.08	27.19	27.16	26.56	27.13	27.02
4	Extrusion	22.38	21.57	22.55	22.19	21.42	22.02
5	Barrel Vacuum	58.07	57.59	59.56	58.59	59.12	58.59
6	Vacuum Tanker	33.01	33.15	33.11	33.07	33.09	33.09
7	Cooler Tanker	5.31	5.23	5.33	5.36	5.4	5.33
8	Hole	8.32	8.36	8.49	8.41	8.45	8.41
9	Cutting	3.53	3.49	3.5	3.4	3.48	3.48
10	Beling Socket	6.59	7.03	6.42	6.57	7.03	6.73

Day 6

Addis Ababa University
College of Technology and Built Environment (CTBE)
School of Mechanical and Industrial Engineering

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No	Activities	Batch No					
		1	2	3	4	5	Average
1	Raw Material Input	10.29	10.43	9.55	10.59	10.56	10.28
2	Hot Mixer	17.07	17.07	17.01	17.09	17.04	17.06
3	Cold Mixer	26.59	27.13	27.13	27.08	27.12	27.01
4	Extrusion	21.09	21.11	22.17	21.36	21.33	21.41
5	Barrel Vacuum	56.51	56.44	55.57	56.39	56.46	56.27
6	Vacuum Tanker	31.04	31.25	32.09	32.04	31.49	31.58
7	Cooler Tanker	5.11	5.02	5.07	5.08	5.09	5.07
8	Hole	8.42	8.43	8.39	8.51	8.53	8.46
9	Cutting	3.44	3.42	3.51	3.49	3.56	3.48
10	Beling Socket	6.39	6.51	6.53	6.5	7.02	6.59

Day 7

Addis Ababa University
College of Technology and Built Environment (CTBE)
School of Mechanical and Industrial Engineering

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No	Activities	Batch No					
		1	2	3	4	5	Average
1	Raw Material Input	11	11.5	10.5	10	12	11.00
2	Hot Mixer	19.08	19.19	19.07	19.21	19.24	19.16
3	Cold Mixer	27.01	27.02	27.12	27.21	27.17	27.11
4	Extrusion	22.49	21.51	22.11	22.04	22.02	22.03
5	Barrel Vacuum	57.06	57.07	57.05	57.05	57.09	57.06

6	Vacuum Tanker	33.02	33.59	33.03	33.04	32.58	33.05
7	Cooler Tanker	5.23	4.58	5.06	5.08	5.09	5.01
8	Hole	8.02	8.11	8.19	8.17	8.15	8.13
9	Cutting	3.54	3.57	3.58	3.59	3.57	3.57
10	Beling Socket	6.39	6.47	6.43	6.51	6.55	6.47

Average

Addis Ababa University
College of Technology and Built Environment (CTBE)
School of Mechanical and Industrial Engineering

My name is Ephrem. I completed an MSc in Industrial Engineering and am working on my thesis to partially fulfill the requirements for the Master of Science degree in Industrial Engineering at the College of Technology and Built Environment, Addis Ababa University. This form is used to collect data through observational methods for my thesis, Enhancing Production Process Efficiency through Value Stream Mapping and Discrete Event Simulation: A Case Study of ECWC-GIW.

No	Activities	Day Average							
		1	2	3	4	5	6	7	Cumulative Average
1	Raw Material Input	9.58	8.54	10.17	11.00	10.01	10.28	11.00	10.11
2	Hot Mixer	18.34	17.02	19.06	18.58	18.46	17.06	19.16	18.24
3	Cold Mixer	27.06	23.07	27.15	27.51	27.02	27.01	27.11	26.56
4	Extrusion	21.51	20.01	22.09	22.07	22.02	21.41	22.03	21.59
5	Barrel Vacuum	56.01	50.10	58.08	59.06	58.59	56.27	57.06	56.45
6	Vacuum Tanker	32.04	29.59	33.38	33.46	33.09	31.58	33.05	32.31
7	Cooler Tanker	4.65	3.48	6.35	5.53	5.33	5.07	5.01	5.06
8	Hole	8.02	6.02	9.04	8.85	8.41	8.46	8.13	8.13
9	Cutting	3.44	2.53	4.38	3.50	3.48	3.48	3.57	3.48
10	Beling Socket	6.57	4.33	7.06	6.75	6.73	6.59	6.47	6.36

2. Capacity and Improved Result

No	Process	Suggested Dist. (Gamma)		Capacity (units/hour)
		Alpha	Beta	

1	Raw Material Input	189.635	0.0533	5.93
2	Hot Mixer	507.687	0.0359	3.29
3	Cold Mixer	343.325	0.0774	2.26
4	Extrusion	959.007	0.0225	2.78
5	Barrel Vacuum	405.780	0.1391	1.06
6	Vacuum Tanker	629.641	0.0513	1.86
7	Cooler Tanker	38.649	0.1309	11.86
8	Holing	77.166	0.1054	7.38
9	Cutting	49.199	0.0708	17.24
10	Belling Socket	56.267	0.1130	9.43

No	Process	Suggested Dist. (Gamma)		Min	Mostly	Max	Mean	SD	Mean^2	SD^2
		Alpha	Beta							
1	Raw Material Input	233.66	0.022	4.74	5.03	5.4	5.057	0.331	25.570	0.109
2	Hot Mixer	226.05	0.071	15.02	16.24	17.16	16.140	1.073	260.500	1.152
3	Cold Mixer	392.93	0.062	23.07	24.56	25.51	24.380	1.230	594.384	1.513
4	Extrusion	313.70	0.061	18.01	19.59	20.09	19.230	1.086	369.793	1.179
5	Barrel Vacuum	411.17	0.102	40.01	42.06	44.16	42.077	2.075	1770.446	4.306
6	Vacuum Tanker	224.64	0.133	27.59	30.31	31.46	29.787	1.987	887.246	3.950
7	Cooler Tanker	11.92	0.416	3.48	5.06	6.35	4.963	1.437	24.635	2.066
8	Holing	97.69	0.058	5.02	5.99	6.04	5.683	0.575	32.300	0.331
9	Cutting	21.39	0.094	1.53	2.1	2.38	2.003	0.433	4.013	0.188
10	Belling Socket	105.86	0.037	3.53	4.11	4.26	3.967	0.386	15.734	0.149

3. DES Current Model Output

3:43:28PM **Category Overview** January 5, 2026

Values Across All Replications

Process Model

Replications: 20 Time Units : Hours

Key Performance Indicators

System

	Average
Number Out	9

Replications: 20 Time Units: Hours

Entity

Time

VA Time

	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Entity 1	2.8103	0.01	2.7767	2.8589	2.6315	2.9683

NVA Time

	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Entity 1	0.00	0.00	0.00	0.00	0.00	0.00

Wait Time

	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Entity 1	5.5535	0.84	0.8588	8.6884	0.2836	16.7559

Transfer Time

	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Entity 1	0.00	0.00	0.00	0.00	0.00	0.00

Other Time

	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Entity 1	0.00	0.00	0.00	0.00	0.00	0.00

Total Time

	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Entity 1	8.3637	0.85	3.6454	11.5032	2.9824	19.4980

Other

Number In

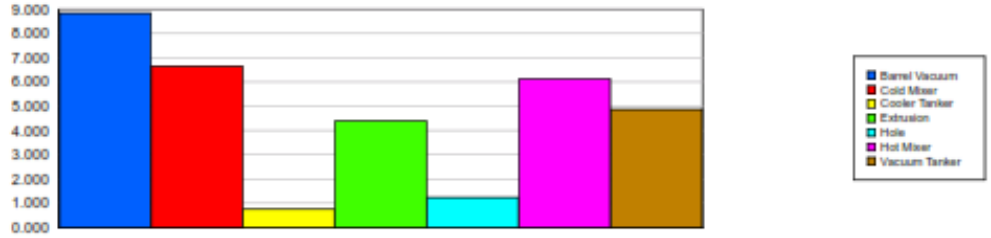
	Average	Half Width	Minimum Average	Maximum Average
Entity 1	19.2500	2.41	12.0000	29.0000

Number Out

	Average	Half Width	Minimum Average	Maximum Average
Entity 1	8.8500	0.53	6.0000	11.0000

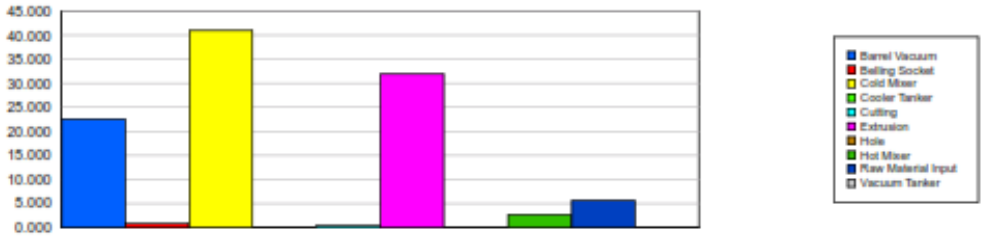
Accumulated Time

Accum VA Time	Average	Half Width	Minimum Average	Maximum Average
Barrel Vacuum	8.8455	0.48	6.7066	10.3309
Cold Mixer	6.6425	0.56	4.4067	9.0437
Cooler Tanker	0.7460	0.04	0.5085	0.8871
Extrusion	4.3806	0.20	3.2819	5.1559
Hole	1.2342	0.09	0.8045	1.5952
Hot Mixer	6.1139	0.79	3.9450	8.7418
Vacuum Tanker	4.8668	0.30	3.2900	5.9719

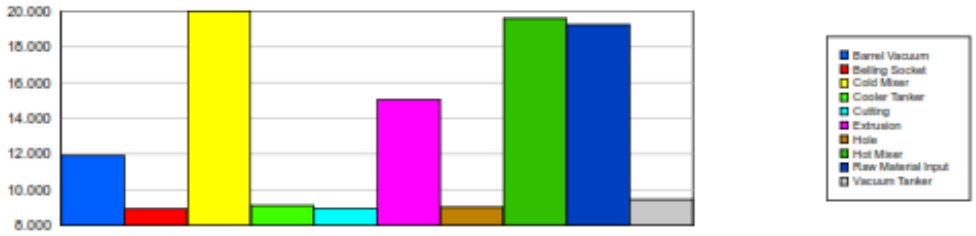


Accumulated Time

Accum Wait Time	Average	Half Width	Minimum Average	Maximum Average
Barrel Vacuum	22.5032	3.68	3.1362	35.3179
Belling Socket	0.9339	0.06	0.5744	1.1382
Cold Mixer	40.9639	10.05	3.7457	89.2931
Cooler Tanker	0.00	0.00	0.00	0.00
Cutting	0.5111	0.03	0.3382	0.6223
Extrusion	31.8785	6.36	2.5874	56.8530
Hole	0.00	0.00	0.00	0.00
Hot Mixer	2.6311	1.16	0.00	11.5954
Raw Material Input	5.5538	1.32	2.1210	10.5542
Vacuum Tanker	0.00	0.00	0.00	0.00



Number In	Average	Half Width	Minimum Average	Maximum Average
Barrel Vacuum	11.9000	0.52	9.0000	14.0000
Belling Socket	8.9000	0.55	6.0000	11.0000
Cold Mixer	20.0000	2.60	13.0000	29.0000
Cooler Tanker	9.1000	0.59	6.0000	11.0000
Cutting	8.9500	0.58	6.0000	11.0000
Extrusion	15.0500	1.25	10.0000	20.0000
Hole	9.0000	0.57	6.0000	11.0000
Hot Mixer	19.6000	2.64	12.0000	29.0000
Raw Material Input	19.2500	2.41	12.0000	29.0000
Vacuum Tanker	9.4500	0.54	7.0000	11.0000



Number Out	Average	Half Width	Minimum Average	Maximum Average
Barrel Vacuum	9.4500	0.54	7.0000	11.0000
Belling Socket	8.8500	0.53	6.0000	11.0000
Cold Mixer	15.0500	1.25	10.0000	20.0000
Cooler Tanker	9.0000	0.57	6.0000	11.0000
Cutting	8.9000	0.55	6.0000	11.0000
Extrusion	11.9000	0.52	9.0000	14.0000
Hole	8.9500	0.58	6.0000	11.0000
Hot Mixer	20.0000	2.60	13.0000	29.0000
Raw Material Input	19.6000	2.64	12.0000	29.0000
Vacuum Tanker	9.1000	0.59	6.0000	11.0000

Queue

Time

Waiting Time	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Barrel Vacuum.Queue	2.6974	0.51	0.2963	4.5114	0.00	7.5534
Belling Socket.Queue	0.00	0.00	0.00	0.00	0.00	0.00
Cold Mixer.Queue	2.6694	0.49	0.4704	4.6178	0.00	8.2924
Cooler Tanker.Queue	0.00	0.00	0.00	0.00	0.00	0.00
Cutting.Queue	0.00	0.00	0.00	0.00	0.00	0.00
Extrusion.Queue	2.7202	0.52	0.2875	4.7377	0.00	8.4456
Hole.Queue	0.00	0.00	0.00	0.00	0.00	0.00
Hot Mixer.Queue	0.1204	0.04	0.00	0.4401	0.00	1.4551
Raw Material Input.Queue	0.0990	0.03	0.00810599	0.2696	0.00	1.2759
Vacuum Tanker.Queue	0.00	0.00	0.00	0.00	0.00	0.00

Other

Number Waiting	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Barrel Vacuum.Queue	1.6316	0.32	0.1333	2.7733	0.00	7.0000
Belling Socket.Queue	0.00	0.00	0.00	0.00	0.00	0.00
Cold Mixer.Queue	2.9768	0.81	0.4402	6.2936	0.00	12.0000
Cooler Tanker.Queue	0.00	0.00	0.00	0.00	0.00	0.00
Cutting.Queue	0.00	0.00	0.00	0.00	0.00	0.00
Extrusion.Queue	2.1852	0.53	0.2735	4.7117	0.00	9.0000
Hole.Queue	0.00	0.00	0.00	0.00	0.00	0.00
Hot Mixer.Queue	0.1303	0.06	0.00	0.5631	0.00	4.0000
Raw Material Input.Queue	0.1094	0.04	0.00486359	0.2945	0.00	4.0000
Vacuum Tanker.Queue	0.00	0.00	0.00	0.00	0.00	0.00

4. DES Improvement Model Output

4:00:51PM **Category Overview** January 5, 2026

Values Across All Replications

Process Model

Replications: 20 Time Units: Hours

Key Performance Indicators

System

	Average
Number Out	11

Replications: 20 Time Units: Hours

Entity

Time

VA Time	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Entity 1	2.5567	0.01	2.5055	2.5923	2.4151	2.7275

NVA Time	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Entity 1	0.00	0.00	0.00	0.00	0.00	0.00

Wait Time	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Entity 1	4.1310	0.93	1.0833	7.4169	0.00	13.5345

Transfer Time	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Entity 1	0.00	0.00	0.00	0.00	0.00	0.00

Other Time	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Entity 1	0.00	0.00	0.00	0.00	0.00	0.00

Total Time	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Entity 1	6.6877	0.93	3.6756	9.9851	2.4208	16.1434

Other

Number In	Average	Half Width	Minimum Average	Maximum Average
Entity 1	18.9500	2.18	9.0000	30.0000

Number Out	Average	Half Width	Minimum Average	Maximum Average
Entity 1	11.3500	0.57	9.0000	14.0000

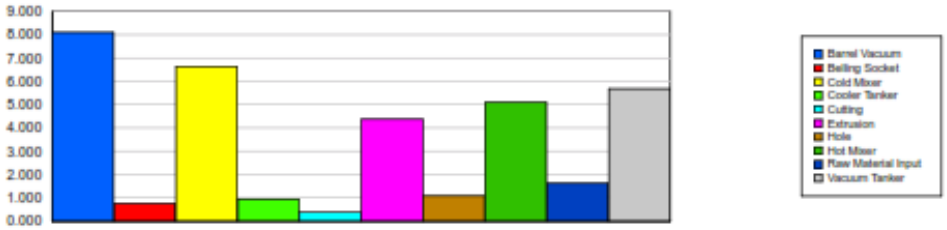
WIP	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Entity 1	6.8476	1.47	1.6531	12.8315	0.00	23.0000

Replications: 20 Time Units: Hours

Process

Accumulated Time

Accum VA Time	Average	Half Width	Minimum Average	Maximum Average
Barrel Vacuum	8.1007	0.42	6.4502	9.4022
Belling Socket	0.7397	0.04	0.5491	0.9106
Cold Mixer	6.6403	0.54	3.2987	8.6334
Cooler Tanker	0.9306	0.06	0.7114	1.1590
Cutting	0.3867	0.03	0.2882	0.4763
Extrusion	4.3711	0.25	2.8452	5.2176
Hole	1.0690	0.06	0.8514	1.3467
Hot Mixer	5.0818	0.55	2.4093	7.9520
Raw Material Input	1.6132	0.17	0.7936	2.4083
Vacuum Tanker	5.6818	0.29	4.6587	7.0434

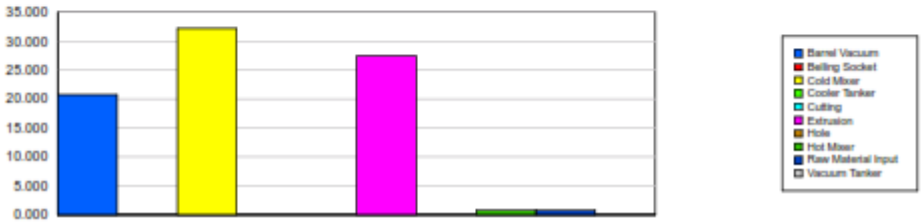


Replications: 20 Time Units: Hours

Process

Accumulated Time

Accum Wait Time	Average	Half Width	Minimum Average	Maximum Average
Barrel Vacuum	20.7319	4.83	3.9865	38.9917
Belling Socket	0.00	0.00	0.00	0.00
Cold Mixer	32.2011	9.26	2.3739	74.9980
Cooler Tanker	0.00	0.00	0.00	0.00
Cutting	0.00	0.00	0.00	0.00
Extrusion	27.4296	6.91	3.2736	49.1997
Hole	0.00	0.00	0.00	0.00
Hot Mixer	0.8239	0.39	0.00	3.0091
Raw Material Input	0.8249	0.30	0.00	2.3917
Vacuum Tanker	0.00	0.00	0.00	0.00

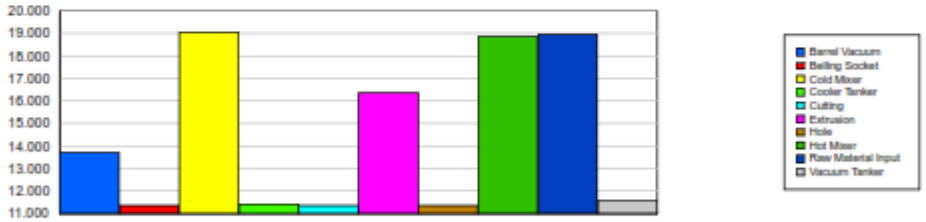


Replications: 20 Time Units: Hours

Process

Other

Number In	Average	Half Width	Minimum Average	Maximum Average
Barrel Vacuum	13.7000	0.76	9.0000	16.0000
Belling Socket	11.3500	0.57	9.0000	14.0000
Cold Mixer	19.0500	2.11	9.0000	30.0000
Cooler Tanker	11.4000	0.58	9.0000	14.0000
Cutting	11.3500	0.57	9.0000	14.0000
Extrusion	16.3500	1.34	8.0000	21.0000
Hole	11.3500	0.57	9.0000	14.0000
Hot Mixer	18.8500	1.98	9.0000	28.0000
Raw Material Input	18.9500	2.18	9.0000	30.0000
Vacuum Tanker	11.5500	0.58	9.0000	13.0000



Number Out	Average	Half Width	Minimum Average	Maximum Average
Barrel Vacuum	11.5500	0.58	9.0000	13.0000
Belling Socket	11.3500	0.57	9.0000	14.0000
Cold Mixer	16.3500	1.34	8.0000	21.0000
Cooler Tanker	11.3500	0.57	9.0000	14.0000
Cutting	11.3500	0.57	9.0000	14.0000
Extrusion	13.7000	0.76	9.0000	16.0000
Hole	11.3500	0.57	9.0000	14.0000
Hot Mixer	19.0500	2.11	9.0000	30.0000
Raw Material Input	18.8500	1.98	9.0000	28.0000
Vacuum Tanker	11.4000	0.58	9.0000	14.0000

5.