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Optimizing Production Line Layout in a Manufacturing Company Using Discrete Event Simulation

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Abstract
Purpose: This study focuses on optimizing the production line for air filter parts in a manufacturing company using discrete event simulation. The current production line is plagued by inefficiencies and bottlenecks, preventing it from meeting peak demands.
Design/methodology/approach: To address these issues, three optimization scenarios were developed and analyzed: Scenario 1 extends machine operation to 24 hours to address limited machine operation time; Scenario 2 incorporates in-process quality inspections to reduce the number of defective products; and Scenario 3 adds workstations and reallocates operators to optimize resource utilization and alleviate bottlenecks.
Findings: Scenario 3 demonstrated the highest efficiency, achieving a 63.16% increase in output, reducing rejects, and balancing resource utilization. This scenario allows the company to meet its peak demand of 550 units within 10 days.
Research limitations/implications: The findings highlight the importance of strategic resource management and workflow adjustments in enhancing production capacity and quality.
Practical implications: The study emphasizes the role of continuous monitoring and iterative improvements in maintaining competitiveness and operational excellence.
Originality/value: The study contributes to the efficiency realm in manufacturing production lines while using discrete event simulation to prevent meeting peak demands.

Keywords: Discrete Event Simulation, Production Line, Efficiency, Bottlenecks, Line Balancing

Introduction

A production line in a factory is a series of machinery, workers, and other personnel who build a product by moving work from one station to the next until the product is completed (Zupan et al., 2015). In a world where manufacturing is fiercely competitive, an effective production process is essential to the productivity of the manufacturing system, thus ensuring the survival of a company. Mebrat et al., (2020) and Velumani et al. (2017a) states that systematic planning and executing variations of processes involved in production results in a reduction of the need for material handling, shortens the lead-time of production operation, and improves general production line productivity.

On the other hand, inefficiencies can cause the occurrence of bottlenecks, ineffective usage of resources, and insufficient space in the production line, which may lead to higher expenses and decreased productivity (Konur et al., 2023). For example, research conducted by Patale et al. (2021) stated that the textile industry experiences a significant amount of downtime, with an average of 800 hours per year, resulting in a 5% decrease in productivity. In another study conducted by Hidayat et al., (2024), the author concludes that 101 experts in the automobile industry who are facing serious problems with production in the United States suffer at least a 5% decrease in production capacity, resulting in a striking average cost of $1.3 million per hour of downtime.

The manufacturing industry in Malaysia is a significant driver of the country's overall income. (Dalenogare et al., 2018). According to Lim et. al (2021)90% of businesses in the nation comprise small and medium-sized enterprises (SME). This means that the productivity of SME manufacturers is crucial to the economic growth in Malaysia. However, the issue plaguing SMEs in Malaysia is the lack of skill development inside manufacturing organizations, and this is mostly caused by an inadequate understanding of the necessary skills, abilities, and knowledge in lean processes. (Abu et al., 2019).

In addition, Tay et al. (2021) Argued that most of the companies in emerging countries are still implementing the traditional way of manufacturing, including Malaysia. Some of the examples are hiring foreign workers in local manufacturers is still prevalent in most of the SMEs in the nation (Hamzah et al., 2020). Furthermore, most of the industrial equipment present in the factories is old, and operators are handling most of the work (Calzavara et al., 2020). The reason for this behaviour is due to the lower income (Calzavara et al., 2020; Hamzah et al., 2020; Kaasinen et al., 2020). The authors argued that SMEs prefer this solution because low-cost manufacturing could lower the cost of the product, hence making it more relevant to stay competitive rather than staying innovative.

Hence, in a low level of digitization in the manufacturing process, improvement in productivity and efficiency of the process is critical in remaining competitive (Rouabah et al., 2023). Optimal balance of production line layout and lean processes is are important factor to be considered so that delays in lead times and bottlenecks could be eliminated.

Despite how crucial it is, manufacturers nowadays are facing major challenges when it comes to constructing an optimal production line. (Boysen et al., 2022). When there is a lot of variation in the number of product families and variants, changes in product designs, introduction of new items, and demand volatility, creating a productive design can become a very difficult process (El-Maraghy et al., 2013). The process of reconfiguring the production and maintenance of facilities can be disruptive, costly, and time-consuming (Kapoor et al., 2021).

Therefore, it is crucial to address the inefficiencies and bottlenecks in the production line to improve operational conditions. This is essential for any company to ensure long-term success and adapt to the constantly evolving business environment, while also enhancing its market position. To solve these issues, this study proposes using Discrete Event Simulation (DES) as an effective method. DES allows for precise analysis and optimization of production processes by replicating a real representation of the systems and experimenting with different variables to predict outcomes without impacting the actual system. By identifying bottlenecks and inefficiencies through DES, companies can implement data-driven solutions to streamline operations, enhance productivity, and reduce costs.

Literature Review

Production Line

A production line refers to a series of sequential operations in a factory that produces goods by moving work from one station to the next until the product is completed (Zupan et al., 2015).

The effectiveness of production line design is crucial for manufacturing efficiency, involving principles such as line balancing, workflow optimization, and the Theory of Constraints (TOC).

However, production lines often face challenges such as material handling inefficiencies, imbalanced workloads, and ergonomic issues. Poorly designed layouts can lead to excessive handling times and increased costs (Erik et al., 2021). For example, inadequate space allocation for workstations can cause congestion, leading to delays and potential safety hazards. Variability in task complexity and operator skill levels can also cause imbalances, affecting productivity and consistency in output (Gabriel et al., 2020). Addressing these challenges requires advanced analytical tools and a comprehensive understanding of production dynamics to formulate effective solutions (Z. Kang et al., 2020).

Line Balancing

Line balancing is a critical concept in production line design. It involves arranging tasks among workstations so that each has an equal amount of work, preventing delays and improving efficiency (Boysen et al., 2022). When tasks are balanced correctly, products move smoothly through the production line without unnecessary waiting times (Kiran, 2019).

Line balancing ensures that each workstation has an equal workload, preventing delays and enhancing material flow efficiency (Hardcopf et al., 2021; Kiran, 2019). Workflow optimization involves arranging operations to eliminate bottlenecks and reduce cycle times, thus improving overall production efficiency (Yelles-Chaouche et al., 2021). Khalid et al., (2021), for example, implemented line balancing techniques to address problems related to shifting bottlenecks that occur in an assembly line, resulting in improved production efficiency. However, achieving perfect balance can be challenging due to varying task times and the complexity of operations (Eriksson, 2020). Continuous monitoring and adjustment are necessary to maintain an effective balance as production demands change.

Theory of Constraints (TOC)

The Theory of Constraints (TOC) focuses on identifying and strengthening the weakest link in the production process, significantly improving system performance (Gupta et al., 2024; Rajini et al., 2018). According to TOC, every production process has at least one constraint that limits its performance (Kan et al., 2020; Ikeziri et al., 2019). By identifying and addressing this constraint, significant improvements can be made.

TOC involves five focusing steps: identifying the constraint, exploiting the constraint, subordinating other processes to the constraint, elevating the constraint, and repeating the process (Gupta et al., 2002). In practice, the method has been applied successfully in various industries. For instance, in a furniture manufacturing production line, the bottleneck was resolved by applying a simulation-based approach that utilizes TOC. This method helped to balance the flow of semi-finished materials, leading to an average production increase of 88% (Gundogar et al., 2016).

Production Line Performance Metrics

Evaluating production line performance is essential for optimizing efficiency, achieving production targets, and maintaining competitiveness. Key performance metrics include daily output, waiting time, and resource utilization. Daily output measures the total quantity of products produced in a day, tracking production targets and identifying bottlenecks (Boysen et al., 2022). High daily output indicates a well-functioning production line, while low output may signal inefficiencies or bottlenecks that need to be addressed.

Waiting time refers to the duration products spend idle at various stages in the production process. Excessive waiting times can lead to delays, increased lead times, and higher costs (Fragapane et al., 2021). For instance, research by Gupta et al. (2024) emphasized the significance of waiting time on the performance of production lines. The research underscored the importance of implementing measures to reduce idle time and enhance the flow of production.

Resource utilization metrics assess the effective use of production resources, such as machines, equipment, and operators. Metrics such as machine utilization, operator utilization, and overall equipment effectiveness (OEE) are commonly used to evaluate resource efficiency (İncekara, 2022; Lakho et al., 2020). High utilization rates indicate optimal resource allocation and minimal waste, while low utilization rates may signify underutilized capacity or inefficiencies in production processes.

Analyzing these metrics together provides a holistic view of production line performance. For instance, a decrease in waiting time may lead to increased daily output and improved resource utilization, indicating a more efficient production process. Continuously monitoring and analyzing these metrics enables organizations to make data-driven decisions, optimize production processes, and achieve operational excellence (He et al., 2018).

Discrete Event Simulation Approach in Manufacturing

Simulation in manufacturing enables precise analysis and optimization of production processes, offering a risk-free environment to test various scenarios. A simulation model replicates real-world systems, allowing experimentation with different variables to predict outcomes without impacting the actual system (Banks, 1998; de Paula Ferreira et al., 2020). Discrete Event Simulation (DES) models state changes at specific events, capturing system dynamics and identifying bottlenecks (De Landtsheer et al., 2016).

DES offers several advantages, including the ability to capture system dynamics, analyze bottlenecks, and experiment with different scenarios to design optimized systems (Mohamad et al., 2019). For example, DES has been used to optimize job scheduling and buffer sizes in automobile manufacturing, significantly improving production efficiency (Kang et al., 2019).

DES is effective in answering "what-if" questions, providing a deeper understanding of manufacturing processes (Dosi et al., 2023). By modeling different scenarios, DES allows for the exploration of potential improvements and their impacts on production performance, enabling data-driven decision-making and continuous process optimization (Brailsford et al., 2014).

DES has broad applications in manufacturing, from optimizing process schedules to assembly line balancing. It has been successfully used in various industries to enhance production efficiency and reduce bottlenecks (Khedri et al., 2015; Omogbai et al., 2016). For instance, DES has been applied to semiconductor manufacturing for capacity planning and comparing dispatching rules, significantly improving productivity (Diaz et al., 2017).

In lean manufacturing environments, DES is crucial for streamlining operations, analyzing material flows, and identifying inefficiencies (Gabriel et al., 2020). The flexibility of DES makes it a powerful tool for continuous improvement and adaptation to changing production demands (Alabdulkarim et al., 2014).

Additionally, DES has been utilized in batch process industries to evaluate current operational states and minimize bottlenecks, leading to more efficient production flows and improved resource utilization (Velumani et al., 2017). In the garment industry, DES has helped in optimizing the layout and scheduling of production processes, significantly reducing downtime and increasing output (Jung et al., 2022). The summary of the application of DES from previous studies is presented in Table 1.

Table 1: Summary of the Application of DES from Previous Studies

Application of DES	Study	Outcome
Job scheduling and buffer sizes optimization	Kang et al., 2019	Improved production efficiency in automobile manufacturing
Answering "what-if" questions in manufacturing processes	Dosi et al., 2023	Deeper understanding of processes and continuous process optimization
Capacity planning and dispatching rules comparison in semi-conductor manufacturing	Diaz et al., 2017	Improved productivity
Streamlining operations and analyzing material flows in lean manufacturing	Gabriel et al., 2020	Identified inefficiencies and enhanced production efficiency
Evaluating operational states and minimizing bottlenecks in batch process industries	Velumani et al., 2017	More efficient production flows and improved resource utilization
Optimizing layout and scheduling in the garment industry	Jung et al., 2022	Reduced downtime and increased output

This literature review highlights the importance of effective production line design and the role of simulation, particularly DES, in optimizing manufacturing processes. Key principles such as line balancing, workflow optimization, and the Theory of Constraints are essential for enhancing productivity and minimizing inefficiencies. Production line performance metrics like daily output, waiting time, and resource utilization provide valuable insights into production efficiency.

Simulation provides a valuable tool for analyzing and improving production systems, offering a risk-free environment for testing various scenarios. DES, in particular, has proven effective in addressing bottlenecks, optimizing workflows, and enhancing overall production efficiency across multiple industries. These concepts are highly relevant to the study's focus on optimizing air filter manufacturing using DES, providing a robust framework for improving production line performance and achieving operational excellence.

Methodology

This section details the methods implemented to obtain the results for this study. The methodology comprises data collection, steps in model building, model validation, scenario development, simulation execution, results analysis, and implementation planning.

Case Company

This case study was conducted with an Air Filter Manufacturing Company based in Johor. The company has been operating for more than 40 years. This small to medium enterprise (SME) company is mostly engaged in manufacturing, engineering, and project management.

Based on data provided by the company and semi-structured interviews with the supervisor and operator, the current production line for air filter parts is not operating efficiently. The productivity constraints are significant enough that the peak demand of 550 units cannot be met within the 10-day timeframe during high-order seasons. This limitation prevents the company from maximizing profits during peak periods. Consequently, there is a pressing need to optimize the production line to enhance efficiency, meet peak demands, and improve overall profitability.

Besides that, the total time taken for each of the processes still needs improvement, as it appears that they are struggling to achieve the daily target demand. Currently, there are six workstations on the production line. Some of the tasks required optimization, as there appear to be bottlenecks. Furthermore, some tasks require attention as the resources are not utilized properly. This results in a significant amount of waiting time in the process and leads to delays in production lead time.

In addition, the challenge that the company is facing lies in effectively utilizing resources such as machinery, labor and materials to ensure smooth workflow continuity. The need for a more flexible approach in resource management is critical to avoid waste and improve the overall productivity of the manufacturing process.

Hence, from there, the need for optimization of the workstation layout and process steps is crucial. This will not only reduce the cycle time and improve the productivity of the production line but also benefit by increasing the production rate, which could achieve the targeted daily demand.

The main objective of this study is to enhance the efficiency of the production line of the case company and will be guided by the following aims, firstly, to develop a discrete event simulation (DES) model of the existing production line, next. to evaluate the current production line layout and identify inefficiencies or bottlenecks and lastly, to provide recommendations to improve the existing production line.

Data Collection

The simulation method needs actual information to accomplish this study. Thus, this study uses observation, interviews, and time study to collect all the necessary information. The collected information is unique data that is specifically relevant to the investigation. The collected data relates to both time and volume.

Quantitative data collection approach is used to gather a deep understanding and to assist with research questions. Collecting quantitative information enables researchers to do a wide range of statistical studies, ranging from basic to highly complex, that combine the data (Ahmad et al., 2019). Quantitative data collection according to Basias et al. (2018), is a type of research that uses the methodologies of natural sciences to generate numerical data and concrete facts. The objective is to establish a causal relationship between two variables using mathematical, computational, and statistical techniques (Ahmad et al., 2019; Basias et al., 2018; Fellows et al., 2021).

For data collection, the task is divided into two parts which are primary data collection and secondary data collection. Primary data is collected by gathering some information about the production line through semi-structured interviews with the staff in charge. The information gathered includes some of the components of DES that needed to be included in the simulation software later. The reason a semi-structured interview is chosen, that the interviewer does not simply stick to a predetermined list of questions; however, instead of a straight question and response style, open-ended questions will be used, allowing for a conversation with the interviewee (Snyder, 2019).

The semi-structured interviews aimed to gather detailed insights into the current production line's operations and inefficiencies. The questions focused on identifying bottlenecks, resource utilization, and process flow. The interview questions were adapted from existing literature on production line optimization (Andersson et al, 2013). Below is a sample of the questions used:

1. What are the main bottlenecks in the current production line?
2. How is resource utilization managed in the production process?
3. Can you describe the flow of materials through the production line?

4. What are the current challenges in meeting peak demand?

These questions were tailored to address specific issues within the case company's production line.
Secondary data refers to information that has been previously gathered by individuals or organizations and is easily accessible for researchers to utilize in their analysis and findings (Moser et al., 2018). Document analysis is a method used to obtain secondary data (Snyder, 2019). This data complements the primary data collected through observations and semi-structured interviews. The secondary data used in this study was obtained from several sources, including company reports, historical production data, and existing literature on production line optimization and DES parameters.
The specific types of secondary data used in this study include historical production metrics such as daily output, machine utilization, and defect rates, which provide a baseline for evaluating current performance. Operational reports from the company detailing past efforts to optimize production were also reviewed, along with industry benchmarks and data from previous research studies. This secondary data was instrumental in establishing a baseline for the production line's current performance, providing context for observed inefficiencies, and offering reference points for evaluating the effectiveness of proposed optimization scenarios.
The data collected was analyzed to develop a comprehensive understanding of the current production line's performance and to identify areas for improvement. Key data items analyzed for the study, particularly the DES parameters used, are illustrated in Table 2 below:

Table 2: List of Analyzed Data

Data Item	Description
Production Cycle Time	Time taken to complete one production cycle
Machine Utilization	Percentage of time machines are in use
Operator Utilization	Percentage of time operators are engaged in productive work
Bottleneck Identification	Areas where delays or backups occur
Defect Rates	Percentage of products failing quality checks
Resources Allocation	Distribution of operators and machines across workstations

For Production Cycle Time, this refers to the total time taken to complete one production cycle, from the start of the process to the finished product. By understanding how long it takes to produce a single item, the throughput of the production line and potential delays or inefficiencies can be identified.
Machine utilization measures the percentage of time that machines are in use during the production process. High machine utilization is a good indicator that the equipment is being used efficiently, contributing to higher productivity. On the other hand, low machine utilization might suggest that the machines are often idle, which could be a sign of inefficiencies.
In order to understand how effectively labor is being used in the production process, operator utilization is analyzed. This data measures the percentage of time that operators are engaged in

productive work. If operator utilization is high, it means that workforce is being used efficiently, with minimal idle time. In contrast, low utilization could indicate that workers are frequently waiting for tasks or equipment, suggesting potential inefficiencies in workflow.
Identifying bottlenecks involves finding stages in the production process where delays or backups occur. Bottlenecks are critical points that can significantly slow down the entire production line. By pinpointing these areas, we can focus on specific process improvements to alleviate the bottlenecks and enhance overall throughput. For example, if a particular workstation consistently has a queue of work-in-progress items, it might be a bottleneck that needs to be addressed.
The defect rate measures the percentage of products that fail quality checks and are rejected. High defect rates indicate quality control issues, which can lead to increased waste and higher production costs. By analyzing defect rates, we can identify areas where the production process may be prone to errors or inconsistencies. Reducing defect rates is crucial for improving product quality, reducing waste, and lowering costs associated with rework or scrap.
Resource allocation involves the distribution of operators and machines across different workstations. Effective resource allocation ensures that workloads are balanced, minimizing idle time and maximizing productivity. By analyzing how resources are allocated, we can identify if certain workstations are overburdened while others are underutilized. Adjusting resource allocation can help create a more balanced and efficient production process.

Component of Discrete Event Simulation

DES is one in which the physical system's state changes discretely at random time intervals (Rouabah, 2023). Events are discrete variables of time that frequently occur at random time points in the discrete-time system (Landtsheer et al., 2016). Author Brailsford et al. (2014), stated that activity diagrams or flowcharts of events are more suitable for representing the dynamic properties of the system rather than relying on mathematical equations like differential equations. Hence, the primary objective of discrete event system simulation is the examination of the statistical properties presented by system events. For instance, the quantity of products in a queue awaiting a quality check can be regarded as a state variable, whereas a product that is entering or exiting the line can be seen as an event (Costa et al., 2017).
To build a DES model some components are important and must be included in the model. Components of DES refer to the basic conceptual building blocks of the model. Table 3 below illustrates the components of the DES model, each with its description.

Table 3: List of Components of Discrete Event Simulation (Scheidegger et al., 2018)

Item	Description
Entities	Give details of all objects within the simulation, including a description of their role in the model and a description of all their attributes
Activities	Provide details of entity routing into and out of the activity
Resources	List all the resources included within the model and which activities make use of them.
Queues	Give details of the assumed queuing discipline used in the model (e.g., First in First Out, Last in First Out, prioritisation, etc.). Where one or more queues have a different discipline from the rest, provide a list of queues, indicating the queuing discipline used for each. If reneging, baulking, or jockeying occur, provide details of the rules. Detail any delays or capacity constraints on the queues
Entry/ Exit points	Give details of the model boundaries, i.e., all arrival and exit points of entities. Detail the arrival mechanism (e.g., "thinning" to mimic a non-homogeneous Poisson process or baulking)

Table 3 shows that DES is made up of several important parts that work together to describe and assess complicated systems. To begin, entities are the simulation's main objects. They stand for things like goods, customers, and tools. Each entity in the model has roles and attributes that determine how it acts and interacts with other entities. This replicates how real-life entities go through different steps and processes. Next, actions are the things that entities do or the steps they take. These actions describe how things get into and out of jobs. They are based on real-world operations such as manufacturing steps, inspections, or service processes. Resources, such as the tools, machines, or workers needed to do tasks, are another important factor. The simulation makes a list of all the resources and the tasks that go with them. This shows how the resources are used and points out any potential bottleneck. Queues are the lines of people waiting to do things. There are different ways to use queues, such as First In, First Out (FIFO) or priority. Queues also consider rules like reneging or baulking to follow through, as well as any delays or limits on capacity. Lastly, entry and exit places set the limits of the model by showing where things come into and go out of the system and the rules that control these changes, like arrival processes or exit conditions. When put together, these parts make an accurate and dynamic simulation model that can be used to study and reflect real-world systems.

Steps in Simulation

DES usually models queuing systems as they progress through time, describing entities (people, products, material, etc.) moving through a network of queues and activities and using limited resources during activities (Gabriel et al., 2020; Kuncova et al., 2018; Velumani et al., 2017a). A DES model was developed based on the statistical parameters and characteristics of the Production Line 1 Layout in an air filter manufacturing company. When developing a simulation methodology, especially a DES model, the building process can be first divided into seven phases as stated by (Centeno et al., 2001). The following flowchart shows the step-by-step process in Simulation modelling.

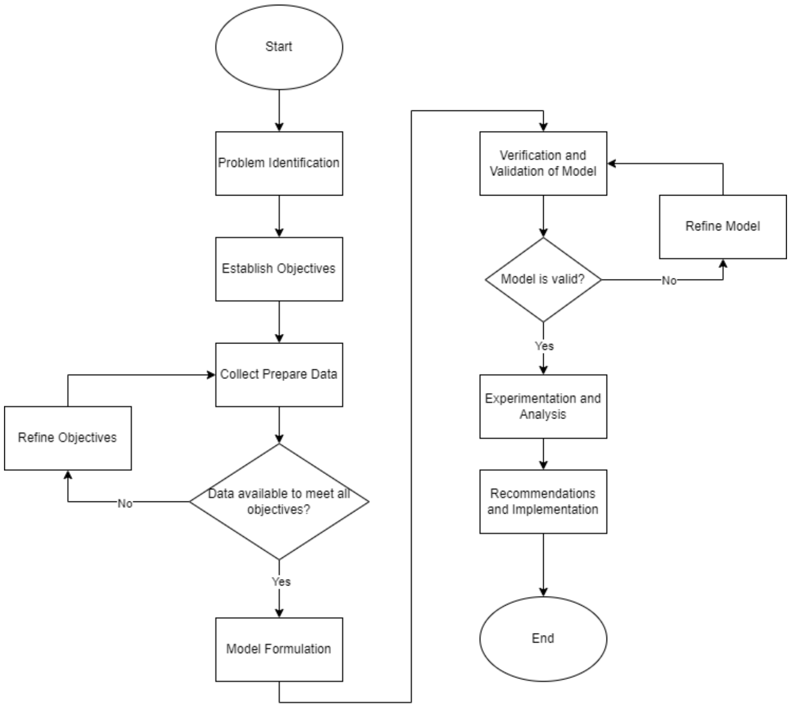

Figure 1: Simulation Modeling Process
Source: Centeno et al. (2001)

Figure 1 shows the flow chart of the steps in building the simulation model. Early in the process, the problem situation and the project description were analyzed and broken down to achieve a uniform understanding. This initial analysis involved studying the combination of data collected through interviews with company staff, which helped to identify key inefficiencies such as bottlenecks, high defect rates, and suboptimal resource utilization in the production line.

Once the problems were identified, it was crucial to establish the objectives of the study to guide the research process. The main objectives included improving production efficiency, reducing waiting times, and lowering defect rates. These objectives were designed to address the specific issues identified in the initial analysis and to enhance the overall performance of the production line.

The next phase involved collecting data necessary for developing a simulation model. Through direct observation, the researcher gathered information on the existing system's operations, including process flow, cycle times, and resource allocation. Additionally, interviews with the operator in charge provided deeper insights into the problems and the flow of the production process. It was ensured that all collected data aligned with the stated objectives. If discrepancies were found, the objectives were refined to better match the actual system requirements.

Following data collection, a detailed formulation of the air filter manufacturing process was carried out. Key stages such as raw material preparation, assembly, testing, and packaging were identified. Each stage was defined as an event with specific start and end points. This detailed breakdown was essential for creating an accurate and comprehensive simulation model.

Simulation Software

The simulation software used for this study is ARENA simulation software, which includes the OptQuest optimization engine. OptQuest is a powerful optimization tool that employs advanced algorithms such as scatter search and tabu search to find the best possible solutions based on the defined objectives and constraints. The data collected will be modelled into the software and then analyzed so that the current production line process can be evaluated. Any inefficiencies and bottlenecks are analyzed by using reports generated from the software so that further process improvement can be made. Some of the modules that were used are Create, Process, Decide, Record and Dispose module.

Validation and Verification

In the next step, the following stage entails the verification and validation of the model. The goal of model verification and validation is to ascertain if the simulation model accurately represents the real system (Djamali, 2018). Next, it is necessary to verify whether the outcomes of the model align with the company's data. To get an effective solution for the simulation experiment that optimizes the productivity of the production process, it is essential to incorporate precise details regarding the conducted tests, which may entail statistical analysis or expert evaluation (Centeno et al., 2001).

To verify, the simulation software Arena was utilized to illustrate that the movement of entities corresponds to the flow of parts in the production line. A simulation model is an accurate depiction of a real system, specifically designed to accurately mimic the behavior of the actual system. This can be accomplished by employing expert judgement. In this scenario, the simulation model will be provided to the interviewee for validation of its appropriateness.

Model validation involves evaluating the statistical accuracy of the simulation model's output by comparing it to the output of the real system. If there are no statistically significant disparities between the data sets, then the model is valid. Conversely, if there is a difference of statistical significance, it suggests that the model is invalid and further investigation is necessary before proceeding with any additional research.

This research complies to the parameters outlined by author Djamali (2018) for the purpose of validation. The author suggests that the Mean Absolute Percentage Error (MAPE) test might be utilized as a validation method to compare the performance of a model with that of a real system. MAPE is a relative measure that quantifies percentage error. This test can be utilized to determine the compatibility between the estimated outcome and the real data. The formulation is as follows:

$$MAPE = \frac{1}{no.of\ Replication} \sum \frac{|Simulation\ Output - Actual\ Output|}{Actual\ Output} \times 100\% \qquad \text{equation (1)}$$

The accuracy of the simulation model was evaluated using the Mean Absolute Percentage Error (MAPE) test. The criteria for assessing the modeling accuracy based on MAPE are as follows: a MAPE value less than 5% indicates that the model is very accurate, a MAPE value between 5% and 10% signifies that the model is accurate, and a MAPE value greater than 10% suggests that the model is not accurate.

Scenario Analysis

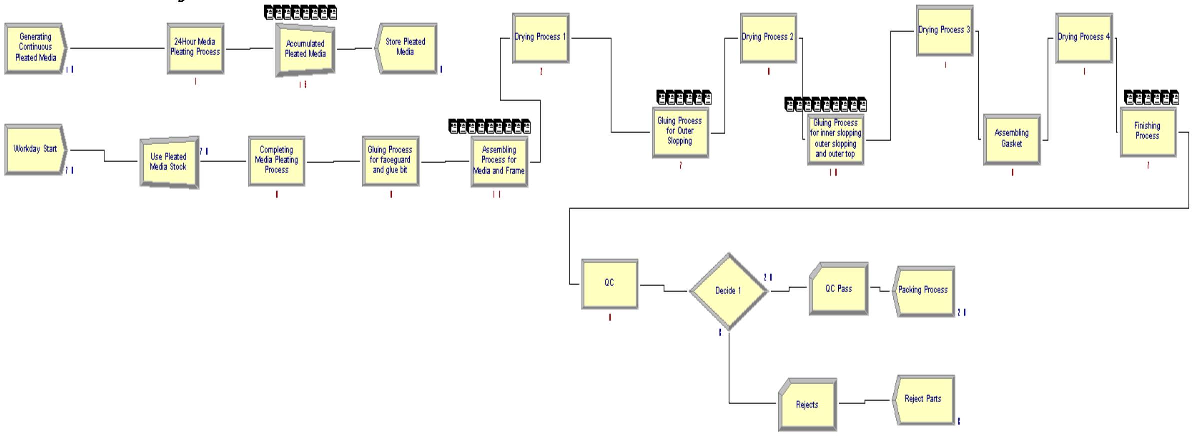

Figure 4: Scenario 1's optimization model
Source: Author's own work

Figure 4 illustrates Scenario 1 which involves optimizing process relative to the base case. In this scenario, the machine operates continuously for 24 hours, producing batches of pleated media intended for the main process. The primary objective of this scenario is to alleviate the bottleneck in the Media Pleating Process Queue and enhance overall production efficiency by expanding the capacity of the Media Pleating Process. This strategic adjustment aims to reduce waiting times and streamline workflow, leading to improved production outcomes.

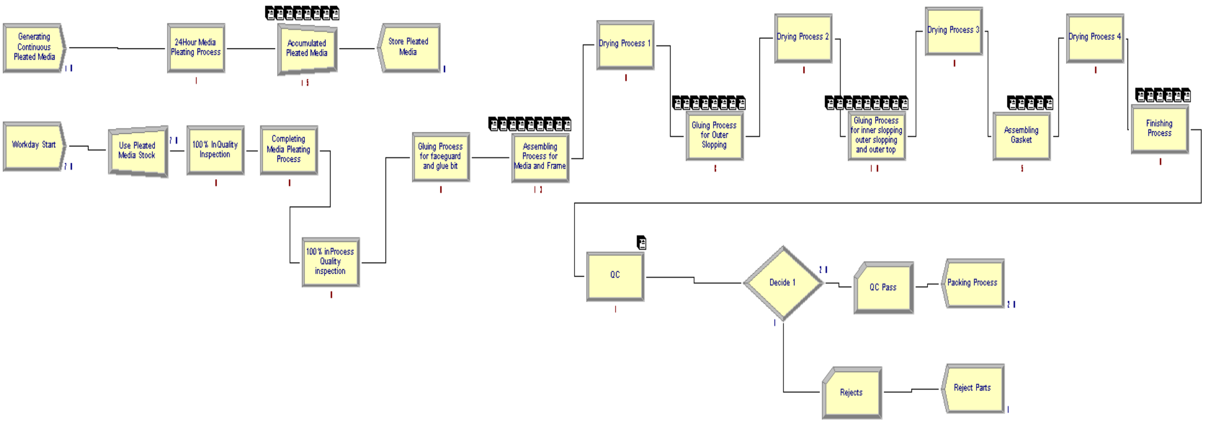

Figure 5: Scenario 2's optimization model
Source: Author's own work

Figure 5 presents Scenario 2, which builds upon the optimizations from Scenario 1 relative to the base case. In this scenario, the improvements from Scenario 1 are maintained, and an in-process quality inspection is integrated into the workflow. The primary objective is to reduce the number of rejected parts and increase the production of quality units. This adjustment addresses the issue identified in the base case, where most rejected units were due to inconsistencies, cracks, and tears in the pleated media occurring during the Media Pleating Process.

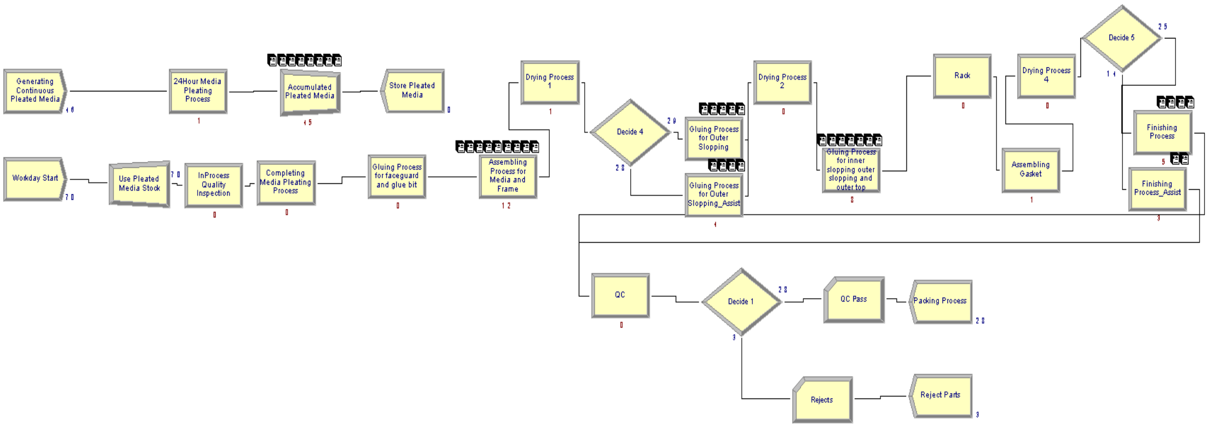

Figure 6: Scenario 3’s optimization model
Source: Author’s own work

Figure 6 depicts the model for Scenario 3, which retains the modifications from Scenario 2 but includes additional workstations and a reallocation of operators. The primary aim of this scenario is to balance the production line, ensuring optimal utilization of operators to minimize waste and enhance overall efficiency. This strategic adjustment is intended to increase the number of outputs generated, thereby improving the production process's effectiveness and productivity.

Findings and Discussions

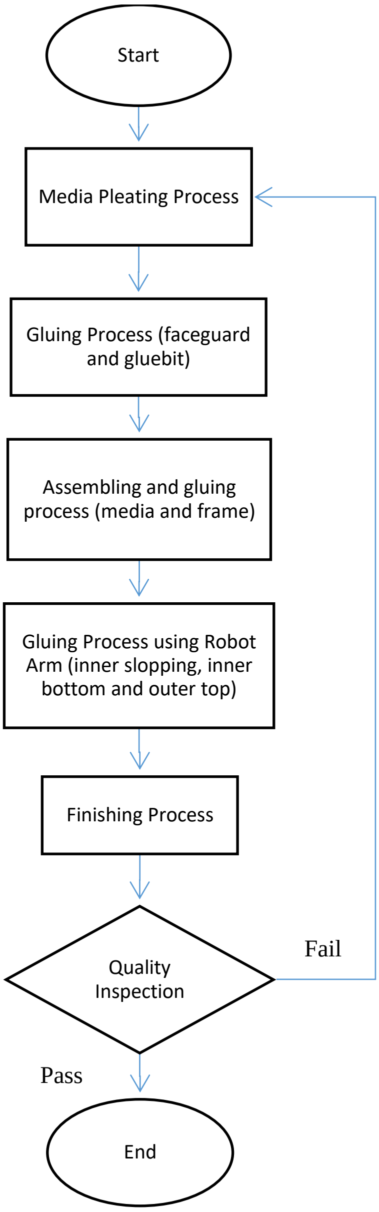

Figure 2: Process Flow of Production Line 1
Source: Author's own work

Figure 2 illustrates the complete manufacturing process of a cartridge designed for placement into an air filter device. The first stage entails utilizing a Media Pleating Machine to fold the media paper into a zigzag pattern. Following that, the media is fragmented into tiny fragments and later affixed to the faceguard, which constitutes the second phase of the technique. Continuing to the third stage, the media is then adhered to its frame and let to rest for the adhesive to harden. In the fourth phase, the inner sloping, inner base, and outer sloping surface are adhered together to securely attach the media structure to the frame. The procedure was carried out using a mechanized appendage. The last stage entails the completion procedure, which includes the removal and cleansing of any surplus adhesive and adhesive residue, as well as the application of labels, among other tasks. Afterwards, the components undergo inspection at the Quality Control station to detect any possible faults. If any components are discovered, they should be stored in the designated area for rejected items for further analysis to see if the product may be repaired. If not, it must be discarded. Parts that do not have any flaws are sent to the packaging stage for additional processing in later stages of manufacturing.

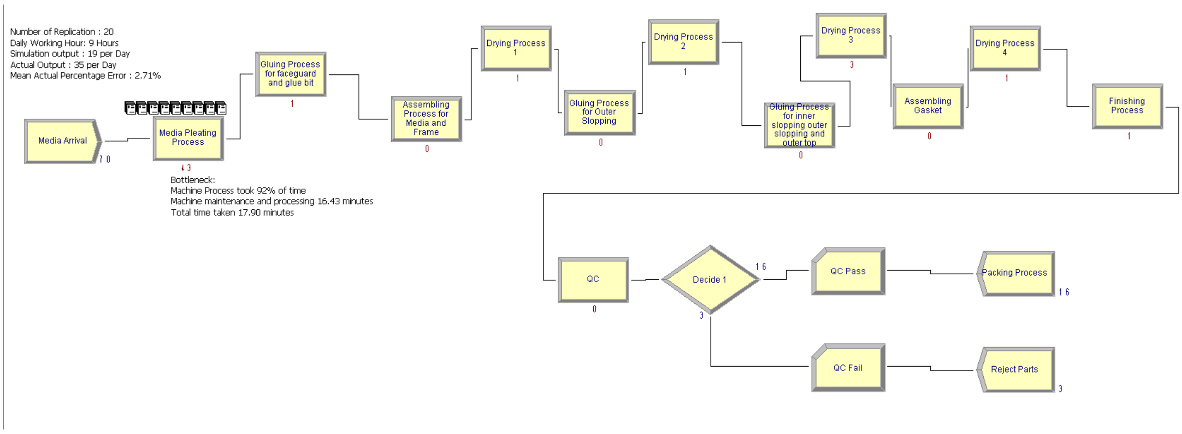

Figure 3: Manufacturing Process of Production Line 1 using Arena Simulation Software
Source: Author's own work

Figure 3 shows the process which had been modelled in the simulation software, known as base case. In the base case, the production line achieved an average output of 19 units with an average waiting time of approximately 3.282 hours across the entire production process. The number of rejected units averaged 3.65 per run. The model was executed for 20 replications, each with a duration of 10 hours, aligning with the daily working time, which includes a one-hour break. Analysis identified the Media Pleating Process as the primary bottleneck due to its high waiting times and the significant number of entities queuing in this process.

For validation, the Mean Absolute Percentage Error (MAPE) was calculated using the actual real-life output of 35 units per day. The MAPE was found to be 2.28% indicating a very accurate comparison between the simulation model and real-life performance considering the MAPE is below 5%. This low MAPE value supports the model's accuracy in predicting the production system's performance.

For verification, face validation was performed by consulting with experts, in this case the production managers and operator, and comparing model behavior against expectations and real-world operations. The experts confirmed that the model accurately represents the production processes, reinforcing its credibility.

The study aimed to optimize the production line layout in a manufacturing company using DES. Three scenarios were tested against the base case to identify improvements in output, waiting times, and resource utilization. The description of scenarios are as follows:

1. Scenario 1: Optimization by Running Machine for 24 Hours and Adding In-Process Quality Inspection
2. Scenario 2: Optimization by Running Machine for 24 Hours, Addition of In-Process Quality Inspection and Implementation of Drying Rack.
3. Scenario 3: Optimization by Adding Workstations and Allocation of Operators.

Table 5 shows the output comparison between Base Case and all Scenarios. Eighteen performance measurements or metrics are used to compare the base case, Scenario 1, Scenario 2 and Scenario 3. These metrics are shown in Table 4 below:

Table 4: List of Key Performance Metrics Evaluated

Key Metrics	Description
Daily Output	measures the total number of units produced in a day.
Waiting Time	measures the duration that products spend idle at various stages in the production process.
Resources Utilization	evaluates the effective use of production resources, including machines, equipment, and operators.
Defect Rates	measures the percentage of products that fail to meet quality standards and are rejected during the production process.

The key metrics used in this study provide a comprehensive evaluation of the production line's performance. The **daily output** measures the total number of units produced in a day, offering insight into the production capacity and efficiency. High daily output indicates that the production line is functioning well and meeting production targets, while low output may signal inefficiencies or bottlenecks that need to be addressed. **Waiting time** measures the duration that products spend idle at various stages in the production process. Excessive waiting times can lead to delays in the production schedule, increased lead times, and higher operational costs. Reducing waiting time is essential for improving overall production efficiency and ensuring timely delivery of products.

Resource utilization evaluates the effective use of production resources, including machines, equipment, and operators. This metric is often expressed as a percentage and includes submetrics such as machine utilization (percentage of time machines are in use) and operator utilization (percentage of time operators are engaged in productive work). High resource utilization indicates that resources are being used efficiently, while low utilization may suggest underutilization or inefficiencies in the production process. The **defect rate** measures the percentage of products that fail to meet quality standards and are rejected during the production process. A high defect rate indicates quality control issues and can lead to increased costs due to rework and wasted materials. Reducing the defect rate is crucial for improving product quality and minimizing production costs.

Table 5: Comparison Key Metrics across Scenarios

Metrics	Base Case	Scenario 1	Scenario 2	Scenario 3
Number Out	19	28	27	31
Pass Quality Check (unit)	15	22	25	29
Rejects (unit)	3	5	1	1
Value-added Time (Hour)	1.4860	1.213	1.296	1.163
Non-Value-Added Time (Hour)	1.0938	1.0938	1.0938	0.2680
Wait Time (Hour)	3.283	3.976	4.598	5.839
Media Pleating Process Queue Waiting Time (Hour)	4.4077	3.3591	0.7035	0.7025
Media Pleating Process Queue Number Waiting	54.1821	26.500	5.3933	5.4067
Media Pleating Machine Utilization	1.0000	1.0000	1.0000	1.0000

Operator 1 Utilization	1.000	0.158	0.159	0.481
Operator 2 Utilization	0.229	0.537	0.538	0.847
Operator 3 Utilization	0.436	0.890	0.889	0.890
Operator 4 Utilization	0.436	0.890	0.889	0.890
Operator 5 Utilization	0.466	0.854	0.855	0.726
Operator 6 Utilization	0.584	0.832	0.840	0.828
Operator 7 Utilization	0.213	0.328	0.327	0.477
Operator 8 Utilization	0.527	0.700	0.701	0.730
Robot Arm Utilization	0.548	0.832	0.840	0.885

Table 5 shows the output comparison between Base Case and all Scenarios. The findings reveal significant improvements in the production line's performance across all scenarios compared to the base case. Each scenario demonstrated different aspects of optimization and their impact on output, waiting times, and resource utilization.

In Scenario 1, the continuous operation of the pleating machine resulted in a substantial increase in output, underscoring the importance of maximizing machine uptime to boost production. However, the increased waiting times indicate the creation of bottlenecks in subsequent processes, highlighting the need for a balance between machine utilization and process flow(Teshome et al., 2024).

Scenario 2 showed that integrating in-process quality inspections and using a drying rack can effectively reduce the number of rejected units while maintaining high output levels. This highlights the value of incorporating quality control measures throughout the production process rather than relying solely on end-of-line inspections.

In Scenario 3, the integration of additional workstations and resource reorganization led to the highest observed output in the study. Figure 7 illustrates a bar chart comparison of Resource Utilization Percentage across all models, demonstrating that Scenario 3 achieved high and balanced resource utilization compared to the other scenarios and the base case. Although this scenario resulted in the highest average waiting times, the trade-off indicates that prioritizing overall system throughput may be more advantageous, depending on specific production goals (Wang et al., 2018).

Upon analyzing the simulation results, it was observed that the "Wait Time (Hour)" in Scenario 3 was the highest among all scenarios, including the base case. Several factors contributed to this outcome. Scenario 3 involved adding workstations and reallocating operators to improve overall production efficiency and resource utilization. While these changes successfully increased daily output and reduced bottlenecks in certain areas, they also introduced new complexities and dependencies in the production process.

One of the primary reasons for the increased wait time is the introduction of additional workstations. While adding workstations can help distribute the workload more evenly, it can also create new points of congestion if not managed properly. In Scenario 3, the addition of new workstations led to increased interdependencies between different stages of the production process. This, in turn, caused delays at various points, as items had to wait longer to be processed by subsequent workstations.

Moreover, reallocating operators to different tasks and stations can sometimes lead to inefficiencies if the new allocation is not perfectly optimized. In Scenario 3, the reallocation of operators, while intended to balance the workload, may have resulted in certain stations being understaffed at critical times, further contributing to increased wait times.

Additionally, the complexity of managing a more extensive and interdependent production process can lead to increased coordination and communication challenges, which might not have been fully captured and optimized in the simulation model. These challenges can manifest as longer wait times, as the system adapts to the new configuration.

One of the most striking results from the analysis was the significant drop in the "Media Pleating Process Queue Number Waiting," which fell from 54.2 in the initial setup to just 5.4 in the improved scenario. This notable change deserves closer examination to understand what caused it and to ensure its accuracy.

Several factors likely contributed to this reduction. First, improvements in how resources were allocated and how workflows were managed led to a smoother and faster production process. By adding more workstations and reassigning tasks to operators, the workload was spread more evenly, which helped reduce the number of items piling up in the media pleating stage.

Additionally, incorporating quality checks during the process allowed for earlier identification and fixing of issues. This proactive approach to quality control likely prevented defects and reduced the need for rework, thereby decreasing the number of items waiting in the queue.

However, the extent of this reduction also raises questions about the accuracy of the model. To address this concern, the model's output was thoroughly reviewed and compared with historical data, and the findings were discussed with company staff to ensure they accurately represented the real-world system. Consistent results across multiple tests further support the reliability of these findings.

It's also helpful to note that similar improvements have been reported in other studies. For example, Jain et al., (2020), observed a significant decrease in queue numbers in entities passing through process in airports after similar adjustments. These findings suggest that the reduction in the media pleating process queue is a likely outcome of the changes implemented.

The pleating machine's full utilization in all scenarios underscores its critical role in the production line. Ensuring that this key resource operates at maximum capacity is essential for achieving high output levels. Efficient resource allocation and reorganization in Scenario 3 demonstrated that strategic adjustments to the production layout could enhance overall system performance without sacrificing quality as stated by authors Chouba et al. (2022) in the study of optimization of resource in hospital through DES.

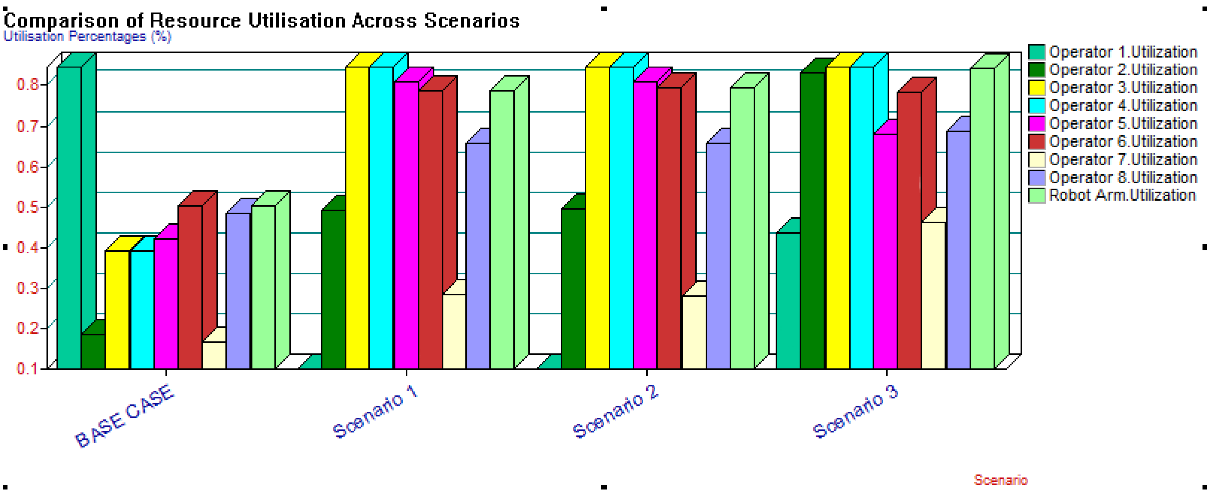

Figure 7: Comparison of Resource Utilization

Conclusion and Recommendation

The study successfully identified and addressed significant bottlenecks in the manufacturing process of B Cartridge F8 air filter cartridges on Production Line 1 and successfully modelled in Arena simulation software with MAPE result of under 5%. Through the application of Discrete Event Simulation (DES), three improvement scenarios were evaluated to enhance production efficiency. Scenario 1, which involved running the pleating machine overnight, resulted in a 47.37% increase in daily output. Scenario 2 further improved efficiency by incorporating in-process quality inspections, and drying racks, yielding a 42.7% increase in output, however 18% higher in quality.

Based on the comprehensive analysis of all scenarios, Scenario 3 is recommended for implementation. This scenario incorporates the improvements from Scenario 2, including continuous operation of the pleating machine and in-process quality inspections, while adding new workstations and reallocating operators for optimal resource utilization.

Scenario 3 demonstrated the highest output, achieving units per day, which marks a 63.17% increase compared to the base case. This scenario also maintained a low reject rate of 1.65 units, ensuring high product quality. The strategic addition of workstations and reallocation of operators effectively balanced the production line, minimizing waste and enhancing efficiency. Consequently, the company can easily meet its highest demand of 550 units, which needs to be achieved within 10 days. This scenario illustrates how optimized resource utilization and workflow adjustments can significantly boost both production capacity and quality.

Scenario 3, while effective in increasing overall production output and reducing certain bottlenecks, resulted in the highest wait times among all scenarios. This outcome highlights the complexities and potential trade-offs involved in optimizing production processes. The introduction of additional workstations and the reallocation of operators, while beneficial in many aspects, also introduced new interdependencies and coordination challenges that contributed to increased wait times. These findings underscore the importance of a balanced approach when implementing changes in production systems, ensuring that improvements in one area do not inadvertently cause inefficiencies in another. Future efforts should focus on fine-tuning the allocation of resources and managing interdependencies to minimize wait times while maximizing overall efficiency.

Making strategic adjustments in resource management and workflow can significantly improve production efficiency and quality. One of the most remarkable outcomes was the reduction in the "Media Pleating Process Queue Number Waiting" from 54.2 to 5.4, achieved through better resource allocation and proactive quality checks. This substantial improvement highlights the potential benefits of optimization in reducing inefficiencies and enhancing overall production performance. Future efforts should continue to focus on refining production processes to maintain and build on these improvements.

While Scenario 3 offers several benefits, such as increased production capacity and improved resource utilization, it also comes with notable disadvantages. The increased wait times and coordination challenges highlight the complexity of optimizing production processes. Additionally, higher initial costs and the need for training and maintenance can pose significant challenges. Balancing these advantages and disadvantages is crucial for achieving sustainable improvements in production efficiency.

In conclusion, adopting the recommended improvements will not only enhance the production line's efficiency but also ensure the company's competitive edge in the market by consistently meeting high customer demands and facilitating future growth.

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