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Research Article

A Discrete-Event Simulation for Optimising Cutting Process Productivity in Furniture Manufacturing Production.

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ARTICLE INFO	ABSTRACT

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In the competitive landscape of furniture manufacturing, the cutting process remains a critical determinant of production lead time and overall operational efficiency. Traditional lot sizing decisions often fail to account for dynamic shop-floor variables, leading to inefficiencies and unpredictable delivery timelines and lead to customer dissatisfaction. This study aims to enhance productivity in furniture manufacturing SMEs by reducing lead time inconsistency and improving on-time delivery performance by optimising cutting operations using discrete-event simulation. The specific objectives include conducting time and motion studies on current cutting processes in SME furniture manufacturing to identify operational inefficiencies and their impact on lead time. To develop a discrete-event simulation model of the existing cutting process, incorporating identified bottlenecks to analyse their contribution to extended lead times. To compare the performance of the optimised simulation model with the baseline process using productivity metrics such as cycle time and throughput. A mixed-methods approach was adopted, combining time studies conducted to pinpoint specific areas of inefficiency, value stream mapping VSM is utilized to map out the production process, and discrete-event simulation using Anylogic software to validate the proposed improvements. Empirical data were collected from a South African SME furniture manufacturing facility. Regression analysis was applied to evaluate the influence of variables such as number of panels, cut length, layout wastage, and operator adjustments on cutting duration. Findings revealed that operator adjustments had the most significant impact on cutting time, with a 32% reduction in adjustments achieved through the proposed optimization model. Simulation results demonstrated a 25% reduction in average cycle time, from 957 seconds to 714 seconds per cut list, validating the model's effectiveness. The linear regression model also enabled accurate forecasting of future demand trends, supporting proactive resource planning. The integration of lean principles with statistical and simulation tools offers a robust framework for optimizing cutting operations in furniture manufacturing. The study recommends the development of an intelligent software system that automates lot sizing and cutting process decisions, thereby reducing lead time and enhancing productivity. This approach holds significant potential for broader application across manufacturing sectors seeking agile and sustainable production systems.

Keywords: Furniture manufacturing, cutting process optimization, lean manufacturing, value stream mapping, simulation modeling, production lead time and discrete-event simulation.

INTRODUCTION

1.1 Global and regional context

The global furniture manufacturing industry contributes over USD 500 billion annually, with small and medium-sized enterprises (SMEs) accounting for more than 70% of production units (OECD, 2020; Koridze, 2022). This sector not only meets growing consumer demand driven by urbanisation and demographic expansion but also plays a pivotal role in global value chains, enhancing economic interdependence and industrial diversification. Within this global landscape, the South African furniture manufacturing sector holds strategic economic significance, contributing approximately 0.95% to the manufacturing GDP and employing 1.6% of the national manufacturing workforce (DTIC, 2021).

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Figure 1.1 illustrates the distribution of South African furniture manufacturers by employee size. Notably, 61% of registered businesses employ fewer than ten individuals, while only 35 businesses employ over 100 people. This distribution underscores the predominance of SMEs and their critical role in sustaining employment and industrial output.

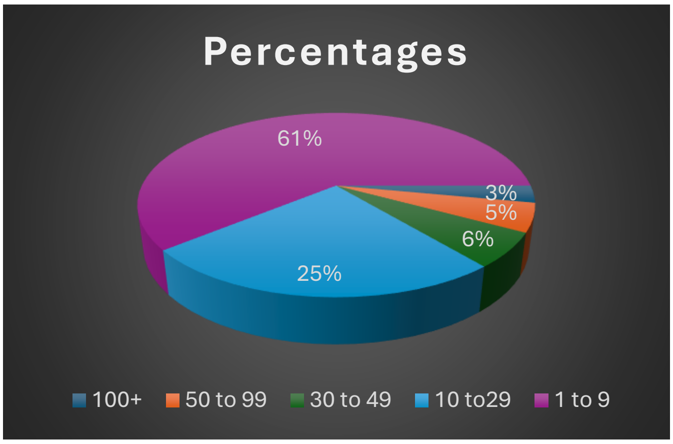

Figure 1.1: Distribution of South African Furniture Manufacturers by Number of Employees (2020)

Despite their economic relevance, SMEs in this sector continue to face operational inefficiencies, particularly during the cutting phase of production. Cutting operations are foundational to furniture manufacturing, directly influencing material yield, production flow, and overall productivity (Ratnasingam, 2022). However, persistent inefficiencies such as machine idle time, poor nesting strategies, and tool wear significantly hinder performance.

1.2 Problem statement

Although advancements in Computer Numerical Control (CNC) and automation technologies have been introduced, many SMEs remain reliant on outdated machinery and lack the analytical bases necessary for data-driven decision-making. As Глотов (2024) notes, these challenges manifest in suboptimal cutting parameters, excessive material waste, and frequent machine downtimes—factors that collectively extend production lead times and compromise operational efficiency. These inefficiencies directly contribute to prolonged lead times, reduced throughput, and delivery delays, thereby undermining SME competitiveness.“Despite the economic relevance of the furniture manufacturing sector, cutting operations continue to suffer from inefficiencies stemming from outdated machinery, suboptimal cutting parameters, and the absence of data-driven decision frameworks. These challenges persist even in the presence of CNC and automation technologies, particularly in SMEs, where resource constraints limit the adoption of advanced optimisation tools” (Глотов, 2024).

1.3 Existing approaches and limitations

Various approaches have been employed to address inefficiencies in manufacturing, including heuristic algorithms (Xia & Shan, 2024), mathematical optimisation (Yang, Zheng, & Wu, 2024), and lean manufacturing principles (Souza & Galhardi, 2022). While these methods have demonstrated potential, they often rely on static models that fail to capture the stochastic nature of real-world manufacturing environments. For instance, heuristic methods may falter under dynamic conditions such as urgent order changes. Moreover, many existing optimisation models are tailored for large-scale operations and are not scalable or adaptable for SMEs.

Discrete-event simulation (DES) has emerged as a vigorous tool for modelling complex manufacturing systems by representing them as sequences of discrete events. DES facilitates the analysis of dynamic interactions among machines, operators, and materials, enabling a more realistic representation of production systems (Wang et al., 2023). However, its application in furniture manufacturing particularly for cutting process optimisation remains underexplored. Furthermore, existing DES applications rarely integrate key performance indicators such as cycle time and throughput, limiting their practical utility in SME contexts (Oliviera,2022).

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1.4 Research gap

Although DES has been extensively applied in sectors such as automotive and electronics manufacturing, its utilisation in furniture production is limited. Existing studies often employ oversimplified models that do not adequately reflect the complexity of cutting operations or focus solely on downstream processes. Furthermore, there is a paucity of research that integrates DES with productivity metrics such as machine utilisation, cycle time, and throughput in a comprehensive framework.

1.5 Research Aim and Objectives

This study aims to enhance productivity in furniture manufacturing SMEs by reducing lead time inconsistency and improving on-time delivery performance by optimising cutting operations using discrete-event simulation.

The specific objectives are:

- To conduct time and motion studies on current cutting processes in SME furniture manufacturing to identify operational inefficiencies and their impact on lead time
- To develop a discrete-event simulation model of the existing cutting process, incorporating identified bottlenecks to analyse their contribution to extended lead times.
- To compare the performance of the optimised simulation model with the baseline process using productivity metrics such as cycle time and throughput.

1.6 Contribution and Significance

This research contributes to the academic discourse by offering a novel application of DES in an underrepresented domain—cutting operations in furniture manufacturing. Methodologically, the study integrates simulation modelling with lean principles and performance analytics, providing a replicable framework for SME adoption. Practically, the findings are expected to support decision-makers in enhancing operational efficiency, reducing waste, and improving responsiveness to customer demand. The study also contextualises its findings within the broader global literature, thereby extending its relevance beyond the South African setting.

1.7 Paper Structure

Section 2 reviews the relevant literature on furniture and cutting process optimisation and simulation modelling. **Section 3** outlines the research methodology, including data collection, model development, and validation procedures. **Section 4** presents the simulation results and performance analysis. **Section 5** discusses the implications of the findings for theory and practice. **Section 6** concludes the study and outlines directions for future research.

LITERATURE REVIEW

2.1. Introduction

The furniture manufacturing industry is undergoing a significant transformation, driven by increasing demand for customised products, reduced lead times, and sustainable production practices (Rame et al., 2023;Wang et al., 2017). These pressures are particularly acute in small and medium-sized enterprises (SMEs), constituting a substantial portion of the sector in developed and emerging economies (Ratnasingam, 2022). Among the various stages of the production process, cutting operations—typically the first and most resource-intensive phase—play a pivotal role in determining overall productivity, material efficiency, and scheduling accuracy (Orlov et al., 2024). This review synthesises the existing literature on the use of discrete-event simulation (DES) for optimising cutting processes in furniture manufacturing, identifying key contributions, methodological trends, and research gaps.

2.2. Furniture Manufacturing and Cutting Process Dynamics

The production flow in the furniture manufacturing process is a complex sequence of operations, including designing, cutting, edge banding, drilling and assembling as shown in Table 2-1, which collectively transform raw materials into finished products that adhere to specific design specifications (Ratnasingam, 2022).

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Table 2-1: Furniture production process

No.	Process Name	Resource	Description
1	Designing	SolidWorks	Design of the final product model using 3D visual software
1	Cutting	Panel saw	Cutting chipboard sheets using a manual panel saw
2	Edge banding	Edge bander	Applying edge bands to straight edges of chipboard elements
3	Drilling	Bench drilling press	Drilling holes in chipboard elements
4	Assembly	Assembly line	Assembling carcasses

In furniture manufacturing, the cutting process is executed using a diverse range of machinery, which typically includes beam saws, CNC routers, and both horizontal and vertical panel saws. The selection of machinery is influenced by several factors, such as the type of material being processed, the required precision, and the anticipated production volume. Studies have shown that inefficiencies in this stage can lead to significant material waste and production delays (Prabukarthi, 2020). The complexity arises from variable order sizes, machine availability, and cutting patterns. which must be optimised to improve productivity.

The cutting procedure generally encompasses several key phases: preparation and loading of materials, the cutting operation itself, machine setup, development of cutting patterns (nesting) and processing of offcuts and waste disposal. Understanding these stages is essential for enhancing productivity and minimising waste, thereby contributing to more sustainable manufacturing practices.

2.3. Overview of Optimization Techniques in Cutting Operations

A variety of optimisation strategies have been developed to enhance cutting operations within manufacturing contexts. Notably, lean manufacturing principles, including value stream mapping (VSM) and the 5S methodology, have been successfully implemented to eliminate waste and streamline workflows (Al-Rifai,2024). VSM serves as a powerful business improvement tool that visualises the complete production process, illustrating both information and material flow based on the current state of the production line (Liu, 2022).

In addition to lean methodologies, mathematical models such as linear programming and integer programming have been employed to optimise cutting patterns and machine parameters. Furthermore, heuristic and metaheuristic algorithms, including genetic algorithms and simulated annealing, have been applied to address complex cutting stock problems (Ranaweera, Rathnayaka, and Chathuranga ,2023)Thus, while existing optimization strategies contribute to enhanced efficiency in cutting operations, further exploration into adaptive methodologies is essential for addressing dynamic challenges in manufacturing environments.

2.4. Discrete-Event Simulation in Manufacturing Systems

Discrete Event Simulation (DES) is an essential tool for optimizing manufacturing processes by effectively incorporating stochastic elements such as machine breakdowns and operator availability, which are often neglected in deterministic models. Its versatility is evidenced by successful applications across various industries, including automotive, electronics, and healthcare, where it enhances production scheduling, layout configuration, and resource allocation, ultimately improving operational efficiency (Ghaleb, 2023; Mitnovitsky et al., 2015). Particularly in furniture manufacturing, characterised by variability and complexity, DES enables detailed modelling of workflows and resource constraints, thus providing a more accurate representation of shop-floor dynamics compared to continuous simulation techniques (Herrera, 2022; Al-Aomar et al., 2020; Mavrothalassitis, 2023).

2.5. Application of DES in Furniture and Woodworking Industries

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Several studies have explored the application of DES in furniture production. Kolny (2023) demonstrated the potential of DES for optimising cutting sequences using Arena software, focusing on reducing idle time and improving machine utilisation. While tools like Arena and FlexSim have successfully simulated cutting operations and material handling, leading to notable improvements such as a 12% increase in throughput in furniture production lines (Bambura, 2020)—the current literature reveals significant gaps. The shortfall of the results of this study is that no workers are included and the wood working industry is highly depended on manual labour. The success of a higher production rate depends on the purchasing of new equipment, e.g., CNC machine, thereby adding costs to the project which is not viable for SME.

2.6. Integrating DES with Productivity Optimisation Techniques

Recent advancements in simulation software, such as AnyLogic and FlexSim, have enabled the integration of DES with statistical and optimisation tools. Linear regression, machine learning algorithms, and multi-objective optimisation techniques are increasingly being used to enhance the predictive accuracy and decision-support capabilities of DES models (Panagiotis et al., 2023).In the context of furniture manufacturing, such integrations allow for the dynamic adjustment, which was shown in the study by Orlov et al. 2024), demonstrated the use of DES combined with Lean Six Sigma to optimise the cutting process in a circular economy framework.

The existing body of literature concerning Discrete Event Simulation (DES) applications in furniture manufacturing exhibits several key limitations. Largely, DES models are applied to downstream processes, such as assembly and packaging, with a notable absence of research focusing on cutting operations. Furthermore, current models frequently operate under idealised conditions, neglecting the integration of real-time disruptions that commonly occur in manufacturing environments. A significant gap also exists in the integration of DES with critical productivity metrics, including throughput, cycle time, and machine utilisation, hindering a comprehensive evaluation of system performance. The unique operational constraints of SMES, such as limited machine capacity and workforce variability, are inadequately addressed in existing research. Addressing these gaps, this study develops a DES model that simulates cutting operations under real-world constraints, employing linear regression analysis and Anylogic software to evaluate the impact of alternative configurations on key performance indicators while emphasising lean manufacturing principles to solve the problem of long lead times. This approach showcases an advanced degree of adaptability to varying customer demand patterns, offering a more flexible and comprehensive approach than studies that concentrate solely on singular product models and may not account for fluctuations in customer demand, by considering the impact of customer demand on the production process.

METHODS

This section outlines the detailed methodology adopted to develop, validate, and analyze a Discrete Event Simulation (DES) model for optimizing the cutting process in a furniture manufacturing SME located in Centurion, South Africa. The methodology is structured into the following key components: research design, conceptual modeling, data collection, simulation model development, experimental design, model validation, results, and discussion.

3.1 Research approach and design

This study is situated within the context of a small-to-medium-sized enterprise (SME) in the South African furniture manufacturing sector. The company specializes in the production of kitchen, bathroom, and office furniture. The production process as seen in Figure 3-1, was decomposed into four major workstations: cutting, edge bending, drilling and assembly. Among these, the cutting stage has been identified as the primary bottleneck, significantly affecting throughput and lead time.

The SME sector in South Africa faces unique challenges, including demand ambiguity, short lead times, and high product variability, which are exacerbated by shifting customer preferences and seasonal demand fluctuations. These constraints necessitate a robust, data-driven approach to production planning and optimization. Discrete Event Simulation (DES) is employed in this study to model the cutting process, capture system dynamics, and evaluate alternative configurations under uncertainty.

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Figure 3-1: Process flow of furniture manufacturing and assembly

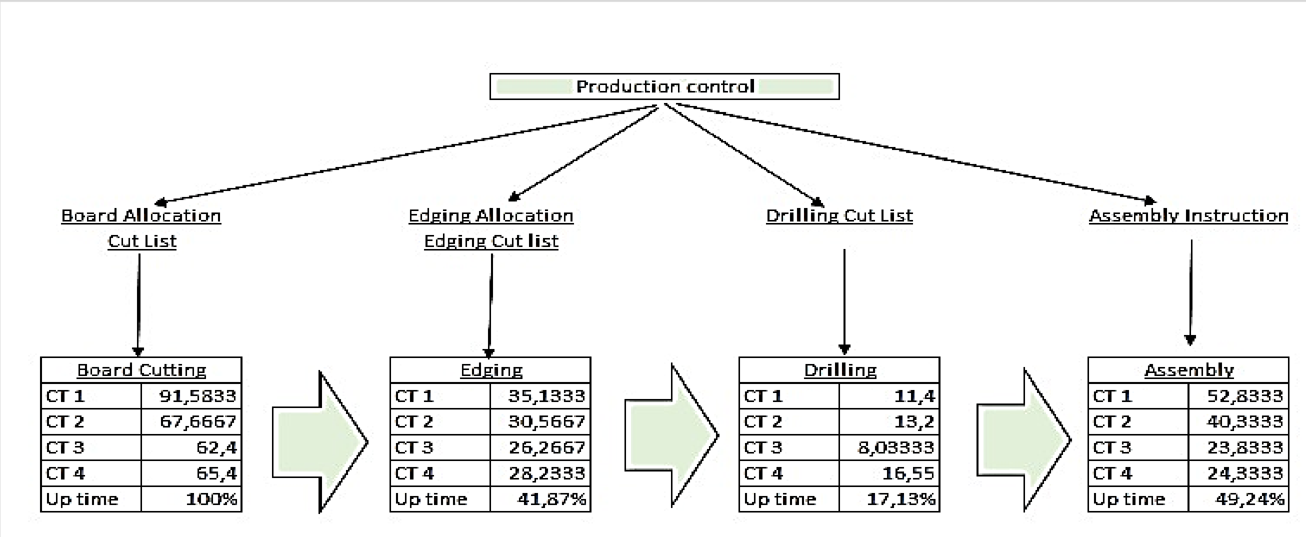

Figure 3.2: Schematic representation of the VSM current state.

Figure 3.2 depicts that the cutting process is the most time-intensive stage in the production workflow, consuming approximately 203% more time than the assembly phase. In contrast, the edging and drilling stages collectively account for only 59% of the time consumed by cutting. Several operational factors contribute to the extended duration of the cutting process. Primarily, the optimization software used in production distributes panel components across multiple sheets, necessitating the completion of the entire cut list before cabinet assembly can commence. Typically, a full cut list comprises around eight sheets, each requiring individual cycle times, which cumulatively result in a prolonged lead time. Given its significant impact on overall production efficiency, it is imperative to concentrate improvement efforts on optimizing the cutting process.

3.2 Conceptual modeling

A conceptual model was developed based on direct observations and process mapping at the case study site. The production process was decomposed into discrete stages, with the cutting process further detailed into sub-processes such as:

- Board Panels arrival
- Queuing
- Place the Board panel on the panel saw
- Machine setup
- Cutting operation

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- Adjustment handling of the board panel and the panel saw .
- Transfer to subsequent workstations

3.3 Data collection and input analysis

Data were collected over three months using both primary and secondary sources:

- Primary Data: Time-and-motion studies, direct observations, and operator interviews.
- Secondary Data: Historical production records and cut lists,

Four categories of data were collected:

3.3.1 Order Data

The order data were structured to reflect actual production time input. Table 3.1 presents a sample of the order input file used in the simulation model.

Table 3.1: Sample Order Data Input

Cutting			
Project	**Seconds**	**No. of Sheets**	**HH:MM: SS**
1	5495	10	01:31:35
2	4060	9	01:07:40
3	3744	7	01:02:24
4	3924	7	01:05:24
5	3499	8	00:58:19
6	4315	9	01:11:55
7	2529	6	00:42:09
8	3627	8	01:00:27
9	2903	6	00:48:23
10	4777	11	01:19:37
	38873	**81**	**10:47:53**
Average time per sheet	479,9136		00:08:00

3.3.2 Processing Time

Processing times were derived from time-motion studies and modeled using a triangular distribution:

- Cutting Time per Panel: Triangular (80, 120, 180 seconds)
- Adjustment Time: Normal (μ = 15, σ = 4 seconds)

3.4. Simulation model development

3.4.1 Simulation Environment

The simulation model was developed using Anylogic 8.7.2, a multi-method simulation platform capable of integrating DES with statistical analysis tools.

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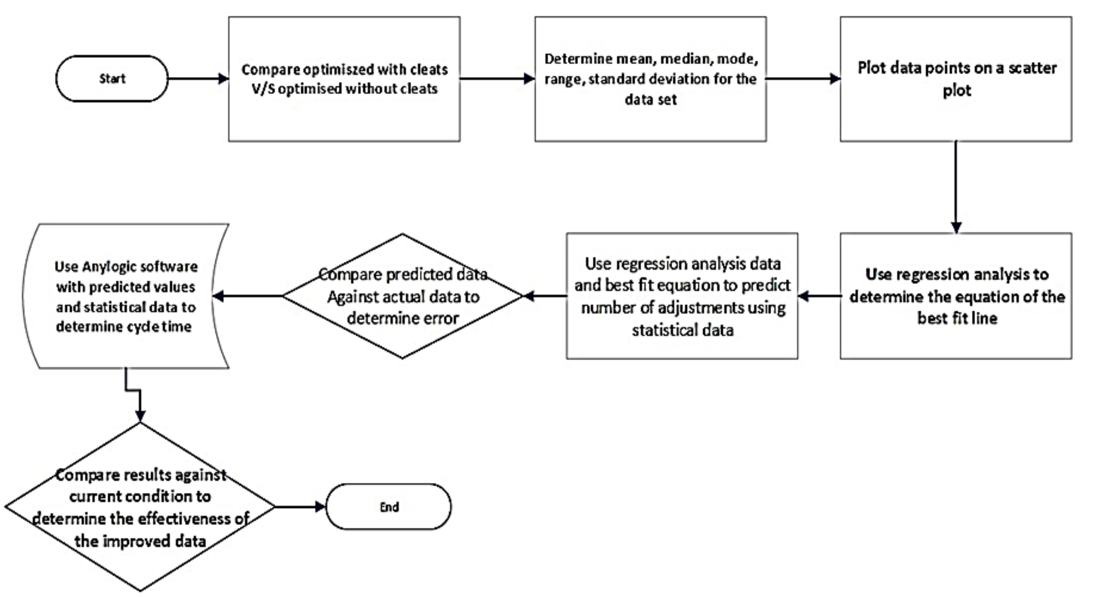

Figure 3-3: A schematic representation of a simulation flowchart.

The figure 3-3 shows the research process involved gathering data from projects with and without cleats, followed by a comprehensive data analysis to quantify adjustment frequency enhancements. Statistical calculations, including mean, median, mode, range, and standard deviation, were performed to understand the dataset's central tendencies and dispersion. A scatter plot was generated to visualize patterns, and regression analysis was used to determine the best-fit equation for understanding trends and correlations. This equation was then used to predict the number of adjustments, and these predictions were compared to real-world data to quantify disparities and errors. The derived equation was validated by applying it to real cut lists to predict cutting times, which were then compared to actual data from previous cut lists.

3.4.2 Model Elements

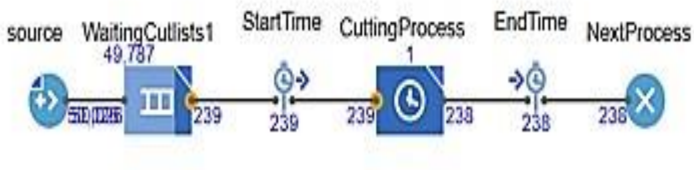

Figure 3-4: Graphical representation of the workflow counter.

Source: This represents multiple cut lists being generated and configured so that preparation time is quicker than cutting time.

Waiting cut lists: This is a representation of a waiting cut list, and it is configured in a manner where it supplies cut lists quicker than the cutting time because, in the workshop, the time to prepare a cut list is quicker than the time it takes to perform the cutting process.

Start Time: This is a zero-point like the start point description in previous chapters; it lapses after the end time starts.

Cutting Process: This begins at the start time and ends at the end time; there is variation in these step-in inputs, and the chapter details these inputs and how the data is processed.

End time: This is triggered after the cutting process.

Next Process: This represents the following process, usually edging.

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The cutting process model has two inputs: the number of panel data parameters, min, max, mean, and standard deviation.

$$NumPanels = roundToInt(normal(1, 61, 13, 1)); \quad (1)$$

BGLM	ARCH	Jarque Bera
F – statistic = 0.1745	F – statistic = 2.538	J. B = 0.4103
Prob. F(2.76) = 0.8402	Prob. F(1.84) = 0.1154	Probability = 0.1845

3.4.3 Model logic and working

The model simulates the arrival of panels, queuing based on FIFO or priority rules, setup and cutting operations, and transfer to downstream processes. The logic includes:

- Dynamic routing first machine.
- Adjustment frequency based on cleats presence

3.4.4 Model output

The simulation outputs include:

- Panel throughput
- Average cutting time
- Machine utilisation
- Adjustment frequency
- Queue lengths

These outputs were exported to Excel for statistical analysis.

3.5. Experimental Design

Three scenarios were simulated:

- Baseline: Current configuration with mixed cleats.
- Scenario A: Cleats grouped separately to reduce adjustments.
- Scenario B: Optimised panel layout using a heuristic algorithm to minimise setup change.

3.6 Verification

Verification was performed through:

- Code walkthroughs
- Step-by-step animation
- Debugging using AnyLogic's trace tools

3.6.1 Validation

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Average cycle time (min)

More pieces, More adustments	More pieces, Few adjustment				
	Occurances %	16	21	26	31
	27	49.97			
	22		50.36		
	17			51.08	
	12				51.33

Total sheets completed in 9600min

More pieces, More adustments	More piecies , Few adjustments				
	Occurances %	16	21	26	31
	27	191			
	22		189		
	17			187	
	12				186

Figure 3-5: Sensitivity analysis, varying panel mix and adjustment frequency

3.6.2 Simulation duration and steady-state consideration

To ensure the dependability and validity of the simulation outputs, the model was executed over a total duration of 9,600 minutes, equivalent to 160 running hours or approximately one standard production month. This extended simulation period was selected to allow the system to reach a steady-state condition, thereby minimising the influence of initial transient behaviours and ensuring that performance metrics reflect long-term operational characteristics. The steady-state assumption is critical in discrete-event simulation (DES) studies, particularly in manufacturing contexts where variability in input parts.

RESULTS

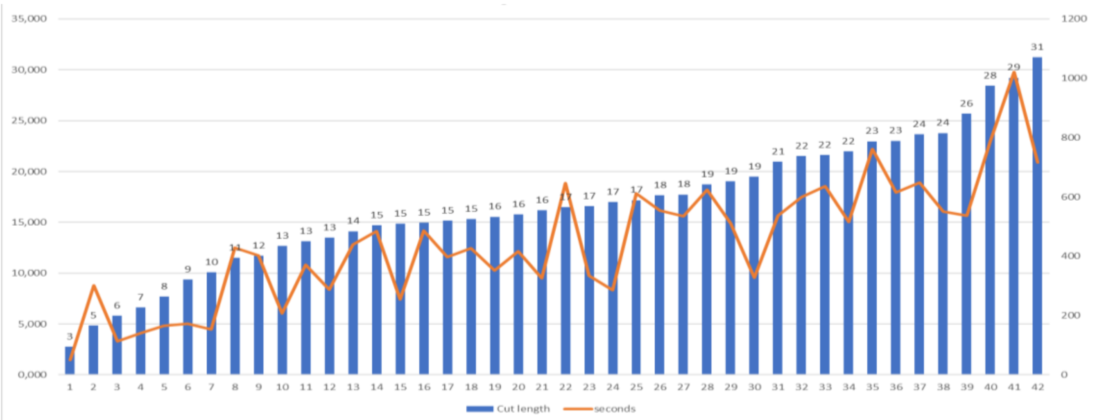

Figure 4-1: Graphical representation of an analysis of the cut length versus duration

Overall, there is a noticeable upward trend in cutting time as the number of panels increases. This suggests that a higher number of panels typically leads to longer cutting times. Some data points, such as points 24, 30, 38, 39, and 42, exhibit notably quick cutting times despite having high cut lengths(± 17M). These outliers may indicate cases where the cutting process was exceptionally efficient or optimised. Investigating these outliers could help identify strategies for improving cutting efficiency. When comparing points 22-25, with similar cut lengths, there is a significant variation of up to 370 seconds in cutting times (approximately six minutes). This variation highlights that factor beyond cut length influence cutting times. These factors could include the layout of the cut list, the number of adjustments required, and other variables. The data suggests that cut list layout is crucial in cutting efficiency. Cut lists with more similar items tend to require fewer adjustments, which can lead to shorter cutting times. Optimising the arrangement of panels within a cut list could be an essential strategy for reducing overall cutting times. The number of adjustments needed during the cutting process is a significant factor in determining cutting time. Identifying why some cut lists require more adjustments than others and finding ways to minimise these adjustments could be instrumental in improving cutting efficiency.

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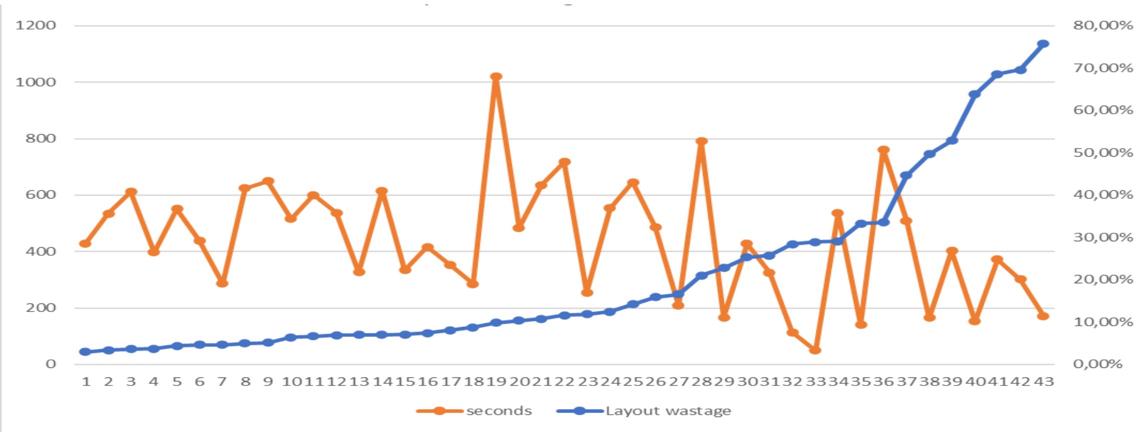

Figure 4.2: Graphical representation of an analysis of the layout wastage versus duration.

The data analysis indicates no direct relationship between layout wastage and cutting duration. Layout wastage varies depending on the specific panels placed on the layout, and the software used is already optimised to minimise waste. However, there is a need to explore other parameters, such as how the number of adjustments made during cutting affects cutting time.

To understand this better, let examine the concept of adjustments and how they are determined in the context of panel cutting with a panel saw:

A panel saw is a machine used to cut large sheets or panels into smaller pieces. It typically consists of a cutting blade and a table or platform where the panels are placed. The operator loads a cut list into the saw's software, which specifies the dimensions and quantities of the desired cuts.

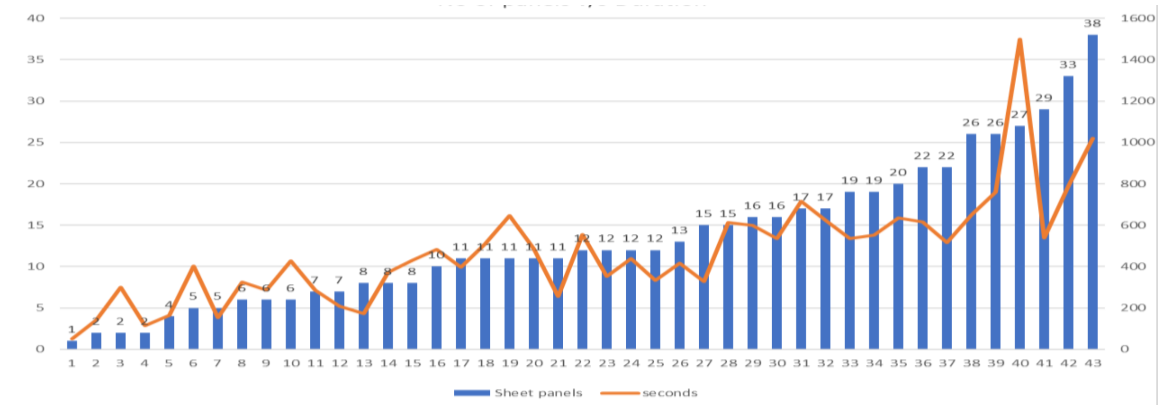

Figure 4.3: Graphical representation of an analysis of the number of panels versus cutting duration

The data indicates that, as the number of panels increases, the cutting duration also increases. This suggests a positive correlation between the two variables, which means that, in instances where there are more panels to cut, the cutting process takes longer to complete. This shows that the key to reducing cycle times lies in the reduction of number of panels cut per sheet.

There are some data points (for example, 25, 27, and 41) where the cutting time is relatively quick, even though the number of panels is high. These points may represent exceptional cases where the cutting process was more efficient or had specific conditions that reduced the cutting time.

Investigating these cases further could provide insights into optimising the cutting process. Variability points 17-21 have the same number of panels, but their cutting times vary significantly by over 250 seconds (4 minutes). This indicates that factors other than the number of panels influence the cutting duration. Some cut lists have more similar items and, as a result, have shorter cutting times. This suggests that the composition of the panels in a cut list can

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significantly impact cutting efficiency. If specific panels can be grouped or processed in a more efficient sequence, it could help reduce overall cutting times.

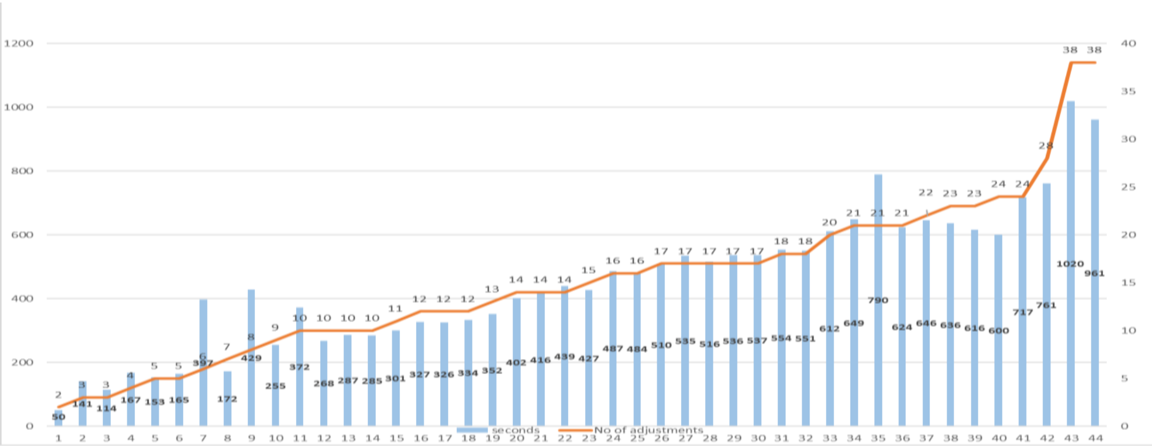

Figure 4.4: Graphical representation of the analysis of the number of panels versus duration.

Number of adjustments and cutting time: The data shows a clear relationship between the number of adjustments made during the cutting process and the resulting cutting time. When more adjustments are required, cutting time tends to increase, indicating that adjustments can significantly contribute to extended cutting times. It was noted that there were four instances where the cutting time was out of range due to minor breaks. These outliers may have occurred due to unforeseen interruptions or issues during the cutting process and should be considered separately from normal operations. Given the observed relationship between adjustments and cutting time, the need to conduct a more detailed analysis of the number of adjustments has been identified. Understanding why some cut lists require more adjustments than others is crucial for process optimisation.

-The cut lists with the most adjustments have many small pieces (cleats) and larger pieces included, and mostly require adjustment on both length and width.

-This is due to the nature of the software, which minimises material waste.

4.1 Data-Driven optimisation via Excel-based analysis

Analysis was conducted on another two projects where the cleats were optimised separately, and the results were as follows.

4.1.2 Scenario A (Cleats Separated)

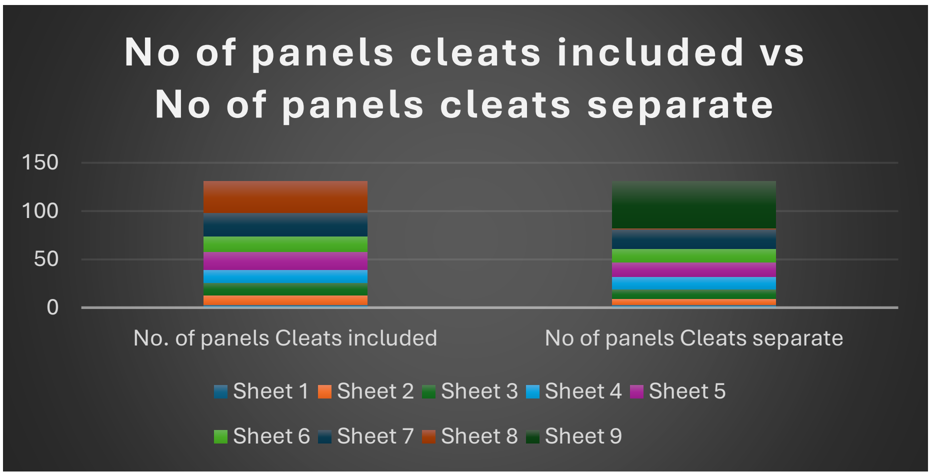

Figure 4.5: Graphical representation of the number of panels with cleats included vs the number of panels with separate cleats

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The total sample size comprises 131 panels, providing a consistent baseline for comparison. This uniform panel count ensures that any observed differences are attributable to the cleat configuration rather than variations in overall panel quantity.

The visual representation clearly compares the two panel types, effectively communicating the project's strategy to group cleats separately rather than incorporating them directly into the panel structure. The project uses the same number of panels, amounting to a total of 131 panels, with the distinctive feature of cleats being grouped separately.

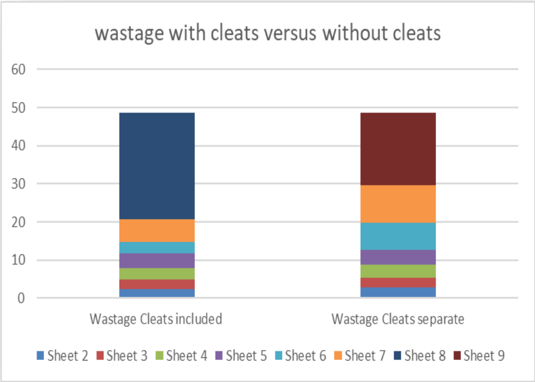

Figure 4.6: Graphical representation of wastage with and without cleats.

The total sample size comprises 131 panels, providing a consistent baseline for comparison. This uniform panel count ensures that any observed differences are attributable to the cleat configuration rather than variations in overall panel quantity.

The visual representation clearly compares the two panel types, effectively communicating the project's strategy to group cleats separately rather than incorporating them directly into the panel structure

4.1.3 Scenario B (Optimised Layout)

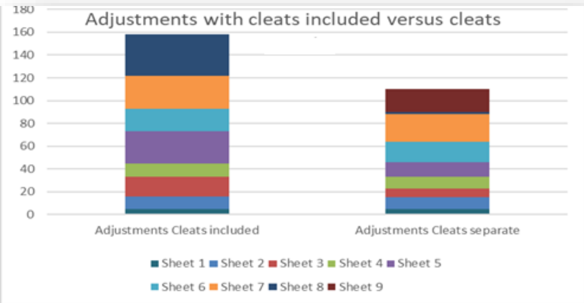

Figure 4.7: Graphical representation of adjustments with cleats included versus cleats separate.

The data analysis highlights a significant achievement in optimising the system, with a notable reduction in the total number of required adjustments. The count decreased from an initial 158 adjustments to a more efficient figure of 110, signifying an improvement of a 30.38% reduction in adjustments

- A reduction in total adjustments from 158 to 110 (30.38% improvement).
- No increase in material waste (wastage remained constant).
- Improved cutting time per sheet from 692.27 to 524.13 seconds on average.

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4.4 Regression Analysis

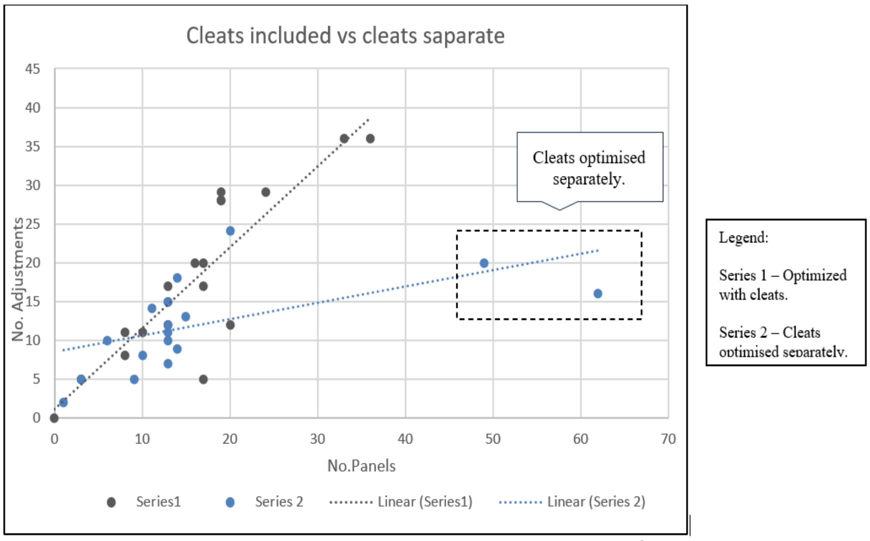

Figure 4.8:Graphical representation of cleats included vs cleats separate.

The regression analysis is consistent with the prior analysis, showing an improvement of 30.38% in the number of adjustments.

- Through the regression analysis, we were able to determine the following equation

$$Y=8.47+0.211x+N(0,4.65) \quad (2)$$

Through the equation, the number of adjustments was predicted.

DISCUSSION

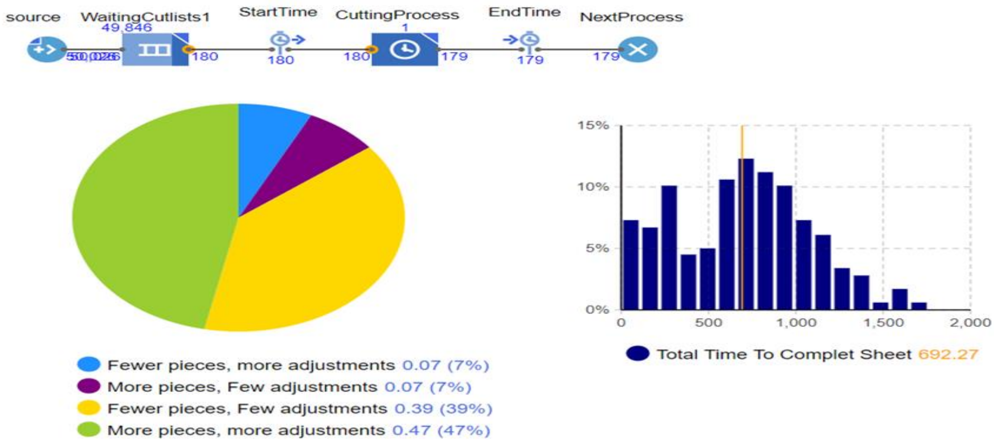

Figure 5.1 The current state (as in state) on simulation

Total throughput =180 sheets in 2076 min OR 36 sheets per shift

Is state on simulation is 692 seconds (11.53 minutes) versus an average cutting time of 492.91 seconds (8.2 minutes) on the 44 cut lists, because the data set on the current project was 49% on the more pieces more adjustments .

Total throughput =180 sheets in 2076 min OR 36 sheets per shift.

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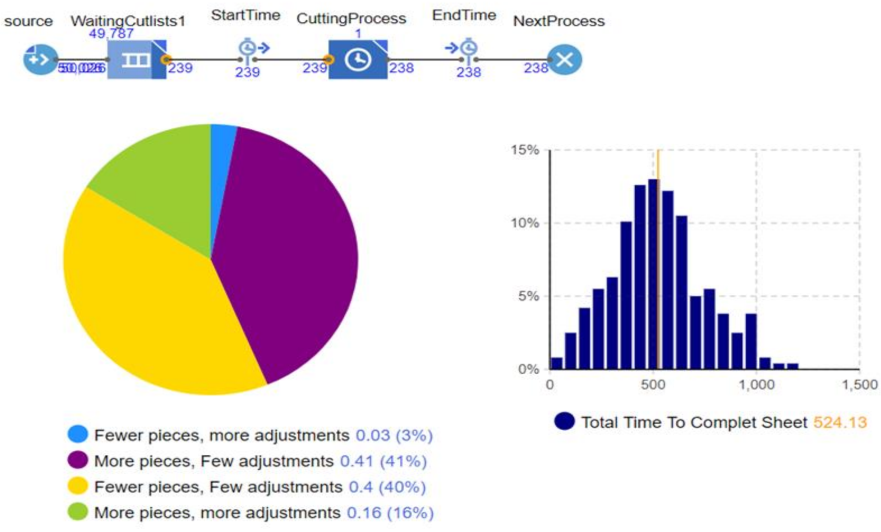

Figure 5.2: The future state on simulation

The model's structure and parameters, detailing the utilization of diverse cut list data for calculating cutting times and adjustments, were thoroughly explained. Model validation and verification revealed a significant 32% improvement in adjustment-related computations within Excel and a 25% enhancement in simulation-based cutting time assessment. Comparing the as-is state, with an average cycle time of 11.53 minutes, to the future state, which demonstrates a reduced average cycle time of 8.6 minutes (equivalent to a total throughput of 238 sheets in 2079 minutes, or 48 sheets per shift), underscores the model's effectiveness in predicting and assessing process improvements.

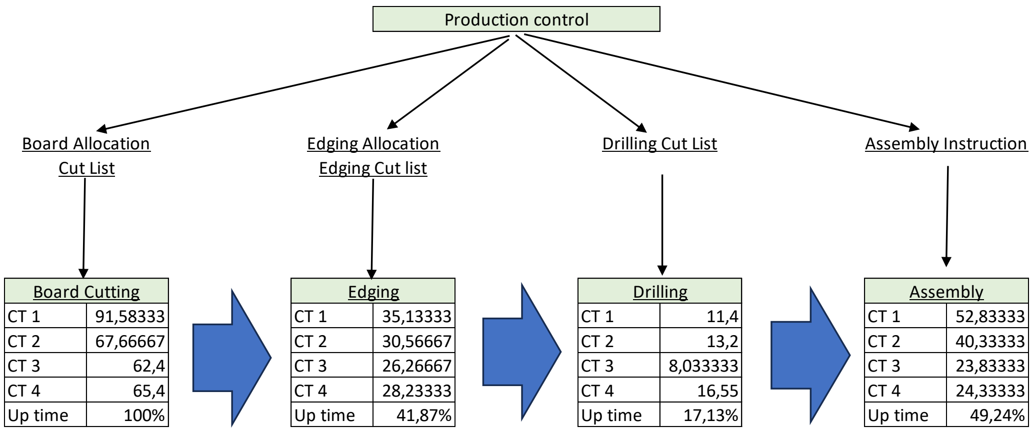

Figure 5-3: VSM of the future state of the furniture manufacturing assembly line:

Average Cycle Time Reduction: The average cycle time was reduced from 71.76 minutes to 53.82 minutes. This indicates that the time it takes to complete a manufacturing or assembly cycle has become more efficient, leading to faster production or assembly.

Assembly Uptime Increase: Assembly uptime increased from 49.24% to 65.65%. This suggests that the assembly process is now running for a higher percentage of the total available time, reducing idle time and improving overall productivity. This indicates that the cycle time has reduced from the initial state to the future state, which is an improvement, as it takes less time to produce each sheet in the future state.

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The quantitative element included a collection of data on key performance indicators (KPIs) such as productivity, lead times, and resource utilisation . Additionally, using Anylogic simulation for the quantitative analysis allowed for the modeling of various scenarios, further enhancing the study's ability to propose optimised solutions for the cutting process, ultimately optimising the whole production line.

CONCLUSION

Optimizing cut list arrangements and minimizing adjustments in the manufacturing process significantly reduces the average cycle time from 692.27 seconds to 524.13 seconds, representing a 25% improvement in cutting time. This solution offers immediate integration for decision-makers in SME furniture manufacturing, enhancing workflow flexibility and enabling more realistic lead time estimations. Limitations of this study include the assumption of constant demand and uniform operator skill levels.   Future work should focus on the development of new software to further streamline and optimize the cutting process.

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