Chapter

Leveraging Lean Manufacturing through Computer Modeling and Simulation for Production Process Improvement

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Abstract

Intensified competition, rapid technological advancements, and shifting customer demands are key catalysts for the global manufacturing landscape. Manufacturing companies that aim to remain competitive have re-evaluated and transformed their business models *via* sophisticated technologies to enhance production efficiency and customer focus. Nevertheless, implementing such innovations often requires substantial investments in infrastructure, training, and system upgrades, which can be challenging for small and medium enterprises (SMEs). The current work examined an SME specializing in aluminum casting products that struggled to reduce the extended production time for high-volume products to meet production planning targets. Discrete-event simulation (DES) modeling served to replicate the current production processes and analyze the system behavior under various production process improvement strategies. A notable 71% reduction in the total production time was required to achieve the monthly planned quantity based on the DES analysis outcomes. Moreover, system dynamics (SD) modeling was employed to evaluate actionable improvement strategies aimed at expanding production capacity and assessing their potential to receive more orders and meet upcoming demand. The SME could meet a demand of 8000 units per month and increase its production capacity by combining overtime and outsourcing strategies. The findings from both simulation techniques offered real-time insights into the impact of proposed improvement strategies on operational and strategic performance measures to understand process optimization and improve production efficiency and capacity with minimal investment.

Keywords: lean manufacturing, process improvement, simulation modeling, discrete event simulation, system dynamics

1. Introduction

Manufacturers, specifically SMEs, encounter significant challenges in improving current production processes. Determining effective strategies to re-evaluate and improve the current production processes has proven to be a complex phenomenon [1]. Hence, it is vital to identify the key areas for improvement. The SMEs must leverage their internal resources and capabilities by transcending existing production processes to consider the need for adaptability to future challenges. Organizational issues can be effectively addressed by implementing appropriate improvement plans and methods [2].

Some companies may relapse into their previous practices, given the complexities involved in initiating a transformation. Implementing an improvement plan requires substantial commitment and investment from the management and workforce. Given its extensive and complicated nature, operationalizing the improvement plan may not guarantee immediate success [3]. The time-consuming attempt to improve current processes to meet demands could extend over several years. A sound understanding of the overall process, its interconnected activities, the potential effects, the necessary inputs, and the anticipated outcomes is integral for a robust operative improvement plan.

Andersson and Bellgran [4] claimed that the success of process improvement is contingent upon the company management's ability to recognize valuable enhancement opportunities. SME managers continue to face key challenges despite the presence of business process improvement methodologies [5]. Manufacturing companies require techniques that complement specific circumstances to achieve their process improvement objectives. Inappropriate selection can disrupt current processes, even when the initial intent is to enhance them. Thus, careful consideration is required when selecting suitable methods.

The nature of the complexities involved and the analysis required for identifying a solution are the important factors influencing the selection of appropriate process improvement methods [6]. Specific contexts and issues must be understood at strategic and operational levels to choose the right process improvement method for a distinctive problem [7]. Companies that prioritize strategic initiatives focus on radical improvements, while counterparts that emphasize incremental improvements tend to concentrate on operational-level initiatives. Based on Malinova et al. [8], most process improvement methods tend to address operational issues but fail to consider the strategic level aspects. This omission can lead to the failure of overall process improvement strategies.

Manufacturing companies that aim to improve their production process must incorporate suitable techniques that evaluate their current processes to identify areas for enhancement, increase the process performance, and facilitate organizational goal attainment. The absence of a universal procedure denoted the need to customize a method that aligns with specific organizational requirements [9]. While some process improvement methods are implemented more frequently and effectively than others, selecting a specific approach depends on its alignment with organizational requirements and its ability to achieve pre-defined objectives.

2. Literature review

Many manufacturing companies have modified their production processes by integrating the pursuit of process improvement strategies with the significance of meeting current business demands. The case studies of Aqlan and Al-Fandi [6] and Mulufeta [10] revealed that reducing cycle time, throughput time, and lead time, the ratio of cycle time to takt time, and work standardization leads to an increase in organizational productivity and efficiency. Furthermore, SMEs that implement process improvement initiatives can reduce the level of work-in-process (WIP) inventory [11], operational cost, and on-time delivery [12] while increasing profit and shareholder value, and generating positive organizational outcomes [5].

The strategies for embedding and sustaining process improvement initiatives without reverting to past practices [13] remain underexplored. The application of changes is a key challenge in process improvement [14]. Antony and Gupta [15] highlighted the lack of managerial commitment and support, inadequate communication, incompetent team, poor training and learning, inappropriate selection of process improvement methodologies and techniques, ineffective rewards and recognition system, scope creepiness, sub-optimal team size, inconsistent monitoring and control, and resistance to change as the top 10 reasons why process improvement efforts fail to increase business performance.

The lack of process improvement approaches renders it challenging to fully meet all requirements [16]. Improving organizational processes can range from minor modifications to major transformations. This spectrum of adjustments relies on adopting an approach that facilitates the execution of planned improvements and yielding of anticipated changes. The changes applied without an organized approach may lack the structure required to determine whether the organization has successfully improved its processes. Overall, using adequate methods designed to identify the root causes of problems, eliminating waste, and addressing variations is key to attaining improvement [2].

2.1 Lean manufacturing implementation

The lean manufacturing approach proved to be the most suitable process improvement method for most companies to resolve encountered problems. Lean manufacturing seeks to increase profitability, customer satisfaction, employee motivation, quality, and low manufacturing costs by identifying and eliminating waste by reducing the waiting time between customer requests and lead time. From the customer's perspective, waste implies activities with no added value [17]. Scholars have used single case study [18–20] and multiple case study [21] methodologies to examine lean manufacturing implementation. The selection between these methodologies depends on the research context.

Surveys are used for investigating lean implementation [22]. Dadashnejad and Valmohammadi [23] employed a set of questionnaires to gather and evaluate employees' perceptions of current processes and operational losses in one manufacturing firm. Lucato et al. [24] also examined lean practices in 51 companies of varying sizes and industrial sectors. The survey revealed key variations in the success of organizational lean initiatives. Belekoukias et al. [25] employed linear regression analysis to explore the relationship between essential lean tools and operational performance measures by modeling the correlation and impact of lean manufacturing practices on 140 manufacturers. Given the focus on subjective opinions rather than objective results, the survey method does not fully capture lean implementation.

Hence, lean implementation studies should emphasize empirical approaches to refine and validate existing theories [26]. Empirical works have delineated how lean implementation affects performance measures. A comparison of the various models integrating the theory of constraints (TOC) with lean manufacturing revealed both elements to be complementary [27]. This theory aims at identifying and addressing production process bottlenecks to optimize throughput, while lean focuses on systematic waste reduction and elimination for improved efficiency.

Value stream mapping (VSM) is vital for facilitating lean implementation [28]. This instrument is used as the initial step in TOC to identify organizational waste while mapping value-adding activities and information flow in current production processes [27]. This robust lean tool was employed by Memari et al. [20] to perform activities analysis and identify the waste caused by inefficient layout and imbalanced production lines, leading to excessive WIP and unnecessary transportation. Meanwhile, Lacerda et al. [11] applied this tool to pinpoint the bottlenecks in generating plastic automotive components. These investigations, which solely focused on specific production processes without considering the overall product flow in the value stream, underscored discrepancies between the operation and available time for each operator.

Notwithstanding, static VSM fails to determine the complexity of actual processes [29], analyzes the component interactions in a production system, and provides the capability to verify or validate proposed system performance pre-implementation [30]. Irani and Zhou [31] claimed that using VSM in isolation may not generate meaningful results in certain scenarios. When applied to multiple products with different production flow patterns, this tool can prove ineffective. Moreover, VSM does not incorporate economic measures of value and adequately depict the impact of inefficient flows on WIP and product throughput, hence limiting its applicability in complex production settings.

Organizations have adopted and implemented lean manufacturing based on their operational settings [32]. Nevertheless, some researchers choose not to use VSM given lean implementation's absence of universality. Mulugeta's [10] time study conducted to identify waste and improve productivity in a garment manufacturing company highlighted excessive movement and transportation of workpieces between workstations as sources of waste. Khan et al. [19] similarly identified problems in an interior design company with Pareto charts and Ishikawa diagrams *via* Kaizen, 5S, and modification of organizational charts, leading to operational improvements.

Many companies struggle to align their approaches with the management control used to coordinate the process inputs, the process itself, and the process outputs and reduce the effectiveness of lean implementation [33]. This problem is exacerbated for SMEs, given their constrained resources [5]. Lugert et al. [32] also critiqued on how most lean implementation studies prioritize operational performance improvement over the key connection between strategic planning and production processes. Singh and Singh [2] recommended integrating distinctive approaches to address these weaknesses and generate optimal outcomes.

2.2 Computer modeling and simulation

Computer modeling and simulation methods are extensively employed to provide a risk-free environment for evaluating the impact of changes in procedures, processes, and information flow to support process improvement initiatives [34]. Based on Buer et al. [35], emergent technologies serve as a key competitive advantage that improves integrated production processes and operational performance. A robust computer model enables companies to address questions on system modeling, explore alternative scenarios testing, visualize processes with clarity, and alleviate financial risks [36].

The information derived from computer simulation facilitates decision-making in lean manufacturing implementation while also driving companies *via* the execution process to attain the desired outcomes [37]. Computer modeling and simulation provide decision-makers with optimal or near-optimal solutions. These operational tools facilitate the quantification of scenarios pre- and post-implementation [38] to prevent the potential failures resulting from adjustments or modifications and delineate system behavior *via* numerical assessment.

2.2.1 DES application

As hand-drawn maps frequently fail to capture intricate details, static VSM encounters limitations in addressing complex processes in the context of lean implementation. An enhanced VSM method incorporating DES was developed to improve operational performance. Combining process mapping and computer simulation is a key to evaluating multiple improvement scenarios and predicting their potential outcomes [39]. This instrument increases the level of detail for a more accurate representation of production processes. Managers who implement the enhanced VSM can identify time-related and other categories of waste to gauge effective management outputs [40].

Abdulmalek and Rajgopal [37] identified high production waiting times as a source of waste by examining the production processes of several grades of steel used in appliance manufacturing. A hybrid production system integrated with total productive maintenance was proposed to effectively reduce the total production lead time and the average inventory levels across all production stations. Likewise, Schmidtke et al.'s [41] case study on the production of exhaust gas purification catalysts revealed high inventory levels and excessive motion due to long production lead time and ambiguity in customer orders. Implementing process integration, controlling the production process at a single step designated as the pacemaker, and maintaining an optimal WIP level in the future state were proposed as three key improvement strategies.

Helleno et al. [29], who examined a manufacturing cell in the Brazilian metal industry, highlighted the need to increase production capacity in the wake of high demand fluctuations. Proportionally increasing current resources, which resulted in the lowest investment cost and greater flexibility, and adopting new process technologies, which required higher investment but achieved better productivity, were the strategies proposed. Omogbai and Salonitis [42] addressed material delays that increase processing times in their case study by re-routing production flow to minimize changeover time and WIP and improve machine utilization. Similarly, Mohd Yusoof et al.'s [43] study involving a Malaysian automotive manufacturing plant indicated an imbalanced workload across assembly workstations as a key challenge. The plant effectively improved production volume and overall productivity by rearranging the layout, adding a workstation, and balancing operator workloads.

Using a combination of lean, simulation, and optimization, Uriarte et al. [44] targeted increased production capacity in a highly variable production environment to improve an automotive component machining line's performance. Despite the lack of details on specific improvement strategies, their approach successfully enhanced material flow, optimized layouts, and integrated the new transport system with existing production to reduce waiting time, unnecessary transport, and inventory levels. Yang et al. [36] examined a fishing net production system with the same approach to determine the optimal combination of five key parameters with minimal performance variance. The case study, which involved the same company as in their previous research, focused on strategic planning decisions. Notwithstanding, this study solely concentrated on the operational level.

2.2.2 SD application

The SD served as a simulation tool for improving process improvement and business performance *via* scenarios that evaluate potential strategic actions for future decision-making. Specifically, Georgiadis [45] examined the impact of capacity planning policies on long-term profitability by structuring an SD model to assess the decision-making process, which balances profit and capacity utilization. Mendoza et al. [46] used the SD model to explore different aggregate production planning strategies and analyze how demand variability and production time affect supply chain performance. Likewise, Deif and El-Maraghy [47] developed this model to explore the effects of implementing production leveling on key performance indicators of inventory levels, lead time, and customer satisfaction.

To simulate the capacity investment and formation patterns of self-interested production agents, Wang et al. [48] constructed an SD model to aid decision-makers in visualizing the dynamics of capacity formation and waste material exchanges, testing different capacity planning and incentivization strategies, and investigating the impact of price disruptions. An SD model was established by Suryani et al. [49] to address corn productivity and production issues resulting from land expansion by adding feedback loops, introducing new parameters, modifying the feedback loop structures, and altering model parameters. Moreover, Filho and Uzsoy [50] integrated an SD model with a factory physics approach to analyze the impact of simultaneous continuous improvement in setup and repair time on manufacturing cycle time in uncertain conditions.

The reviewed SD papers are independent studies that collectively enhance decision-making *via* scenario development. With each study addressing a novel problem, SD models serve to evaluate the impact of strategic actions on key performance indicators. These approaches indicate positive results in improving current performance, albeit with a sole focus on isolated improvement aspects. Potential synergies between strategic and operational levels were left unexamined.

2.2.3 Combination of DES and SD

Both DES and SD varied in their focus and methodology. The DES is stochastic in nature and emphasizes the finer details of a system that generates varying results with each run. Multiple executions and statistical methods are required for this variability, necessitating the analysis of the outcomes. Conversely, SD only requires a single execution to produce consistent results with every run. The inclusion of SD or DES in a process improvement project must be justified by their ability to reduce implementation risks, as computer simulation models incorporate time as a critical factor [51]. It is vital to understand how process changes impact key performance measures for organizational success [39].

The integration of DES and SD is a hybrid approach to harnessing the strengths of both techniques and addressing complex systems that prioritize detailed event-based interactions and dynamic system behaviors. Brailsford et al. [52] categorized types of integration into three categories: (i) automated integration contained within a commercial software package (CSP); (ii) manual integration, literally copying and pasting data from one CSP into another; and (iii) integration using intermediate tools, such as Microsoft Excel. Regardless, the number of comprehensive frameworks outlining the full range of options available to modelers remains lacking. Technical considerations for integrating these methods and the significance of project-specific contexts are key aspects that remain relatively unaddressed [52, 53].

In process improvement, the combined use of DES and SD provides an innovative and comprehensive approach. Bowles and Gardiner's [39] study involving a manufacturer of pre-hung door machinery aimed to improve its design document control process by forming a cross-functional team for prioritization and approval and establishing standard operating procedures (SOP) for the engineering group. These measures effectively addressed 10 out of the 19 issues pertaining to the document control process. The SD was used to supplement the insights gained from process mapping and evaluate the impact of various process improvement scenarios on multiple performance measures during their redesign phase.

Bowles and Gardiner's [39] use of SD supported the recommendations developed *via* process mapping, with additional insights leading to further suggestions for improvement. Notwithstanding, the current SD model served to assess the predetermined strategies for adding production capacity following the optimal capacity value elicited from the process improvement strategy developed *via* DES. A sequential mixed-method approach comprising DES and SD was employed in the following case study, drawing on the methodology outlined by Morgan et al. [53]. This approach was used to evaluate different levels of production process improvement strategies and holistically facilitate the company's exploration of various scenarios.

3. Case study

The case study chose to examine a sample company manufacturing various aluminum casting products. This SME operates a job shop production system comprising three key stages: diecasting, secondary processing, and machining. Following a pre-defined process sequence, production is organized in batches and adheres to standard process cycle times. Products move sequentially through these stages and advance to the next stage only after the batch reaches the predetermined quantity at each stage. The machining processes were identified as bottleneck processes, limiting the overall system capacity, with each bottleneck process having a cycle time of 400 seconds per unit.

The monthly production time available was 28,380 minutes, based on two daily shifts of 10.75 hours each and over 22 working days per month, as per the production planner. The theoretical maximum production capacity was calculated at 4257 units per month with this value. Specifically, the total production time available was divided by the bottleneck process cycle time. The monthly production target was set at 4000 units, which accounted for rejection and downtime. The organizational challenges were evidenced by comparing planned and actual production outputs over 6 months. While the planned quantity remained a fixed quantity each month, the actual production output was found to fluctuate.

The planned targets were not attained despite the implementation of a fully automated high-pressure robotic diecasting process in the production plant. This failure can disrupt delivery schedules, lower customer satisfaction, compel customers to switch to competitors with more reliable alternatives, and undermine the company's long-term competitiveness and market reputation. Notably, companies with extended production time are unable to swiftly adapt to order volume fluctuations, hence reducing operational flexibility. The organizational management should actively seek optimal solutions to improve production process efficiencies.

Companies also strive to increase production capacity and accommodate growing workloads, particularly when current production processes have reached their limits or cannot be scaled further, using relevant strategies. The need for transformative innovations becomes evident with the continuous rise in customer demand. Expanding production capacity potentially enhances the organizational ability to receive more orders and address customer demands. Nonetheless, the complexities underlying production capacity expansion necessitate serious consideration of the expansion time required, the risks related to investments in new facilities and technology upgrades, budget constraints, and current operational capabilities.

4. Methodology

The research flow (refer to **Figure 1**) starts by formulating the problem before developing the research objectives. This step requires a sound understanding of the existing production system and the challenges encountered by the sample company. This method involves determining the performance metrics to measure the system of interest and outlining the performance objectives to be achieved. The subsequent step entails collecting data in the form of input parameters and supplementary details necessary to represent the system.

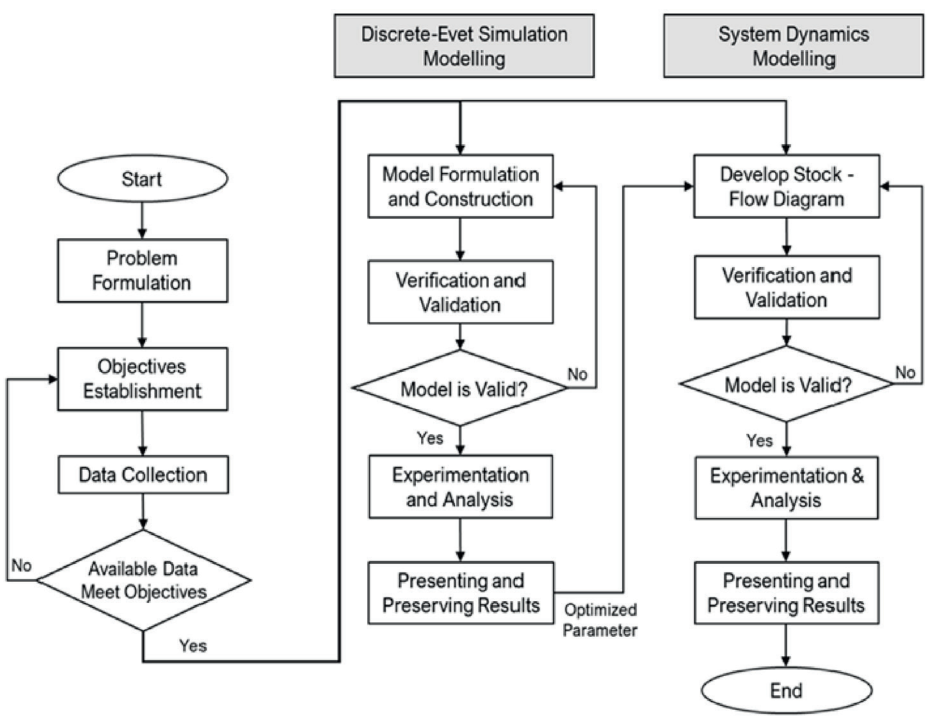

Figure 1.
Research flow framework.

Direct observations made during plant visits, focus group interviews, and the assessment of production reports and process flow charts served as empirical data. Subsequently, a detailed simulation specification and a computer model accurately representing the actual system were developed once the collected data was aligned with the established research objectives. Known as the “base model,” this representation defines the various components in the production processes, their interrelationship, and flow of inputs and outputs throughout the system to ensure that the simulation model encompasses all key aspects. The design phase begins by thoroughly analyzing the system components, which includes the machinery and manpower involved, production flow and sequence, as well as production planning schedules. In this vein, the built computer model reflects the complexities and interdependencies inherent in the actual production environment.

Experiments are then conducted by identifying potential scenarios to explore, adjusting input parameters, policies, and conditions, and estimating model outputs *via* statistical methods. This study provided a sound understanding of the system’s behavior, evaluated different improvement strategies, and measured the impact of changes by running multiple simulations and analyzing the elicited outcomes. With regard to DES, this iterative process also applies to the SD model development. The optimized parameters derived from DES (capacity and throughput time) served as key inputs for SD model construction in addition to using the collected data. These parameters provided key insights into production capacity by calculating the quantity that can be produced during normal production hours and overtime.

5. Results and discussion

The results of this study aimed at evaluating process improvement strategies in improving existing production processes. The study employs an integrated approach, combining DES and SD. This integration offers a comprehensive assessment of both short-term operational performance and long-term capacity planning. By integrating empirical data with simulation models, this approach evaluates the impact of production process improvement strategies and offers practical recommendations prior to implementation.

5.1 Scenario testing of DES model

The simulation results of the “base model” indicate that the system’s average throughput time is 1619.8 minutes, with 1599.1 minutes spent in queues. These findings highlight significant inefficiencies within the system, where transforming a single product from raw material to a finished good takes approximately 16.2 minutes. Consequently, for the sample company to produce 4000 units in a month, a total production time of 64,792 minutes is required. This underscores that the actual production processes are severely impacted by substantial delays caused by prolonged waiting times between production stages. To meet the desired production output, align with planning targets, and optimize capacity, substantial improvements to the existing production processes are imperative.

The base model was modified to assess improvement strategies through scenario testing. In the first adjustment (referred to as the improvement scenario one model), the machinery involving three machines was restructured to resolve bottlenecks at machines two and three. These two bottleneck processes were reorganized to operate in parallel, allowing them to function simultaneously and improving the overall production flow. This modification was based on the similarity between the two processes, with the only difference being the type of cutting performed.

Consequently, the modifications from the model of improvement scenario one were retained, with additional adjustments made (referred to as the improvement scenario two model). The key adjustment involved dividing the created entity into smaller batches, a strategy known as production leveling. The second modification introduced a more flexible approach by subdividing the total entities created into smaller batches when transitioning between modules.

In the following scenario testing, the changes involve maintaining smaller batches for the total production quantity while reverting the arrangement of machines 2 and 3 from a parallel configuration back to the original series configuration (referred to as the improvement scenario three model). The aim of this change is to assess which modification yields the best results. Surprisingly, the simulation outcomes for this scenario testing are significantly better than those of the previous two improvement scenarios.

5.1.1 DES results

Table 1 presents a comparison of the simulation results for the base model and the three proposed improvement scenarios. This analysis offers valuable insights into the impact of each modification on production efficiency by reducing throughput time, waiting time, and the number of WIP while also exploring innovative solutions that can drive substantial productivity gains. Such a comprehensive comparison enables informed decision-making in process optimization. By examining these results, the sample company's management can determine which strategy delivers the most significant improvements before implementation. This analysis highlights the role of data-driven decision-making in enhancing operational performance. The decision to test the improvement strategies focuses on leveraging internal resources and capabilities while aligning them with the company's existing challenges.

The substantial improvements presented in **Table 1**, with improvement scenario three achieving an impressive 71% reduction in throughput time, highlight the effectiveness of the proposed strategies. These efficiency gains allow the sample company to meet its monthly production targets while adapting more effectively to market demands. By optimizing batch sizing through production scheduling, the company can now produce up to 6000 units per month without incurring additional operational costs as well as disrupting the delivery schedules.

By leveraging simulation-based experimentation, the sample company gains a powerful tool to thoroughly analyze its existing production processes. This approach

Performance measures	**Simulation model**			
	Base	**Scenario 1**	**Scenario 2**	**Scenario 3**
Average throughput time (minutes)	1619.8	1192.1	595.2	471.9
Average waiting time (minutes)	1599.1	1171.9	573.6	450.2
Production time required (minutes)	64,792	47,708	23,808	18,876

Table 1.
Comparison of simulation results.

enables a detailed examination of workflows and process bottlenecks, providing insights that would be difficult to achieve through VSM analysis. Using simulation analysis, the company can systematically identify waste and constraints, which often go unnoticed in complex production systems. Eliminating or minimizing these inefficiencies not only streamlines operations but also improves overall productivity.

5.2 Scenario testing of SD model

A stock-and-flow diagram is a quantitative model derived from the interconnections of variables forming a causal loop diagram. It integrates equations and relevant input parameters drawn from production records, management decisions, and optimized outputs generated by the developed DES model, such as throughput times and the maximum units producible within the available monthly production time. This SD model operates on the assumption that the current production processes have reached their capacity limits and cannot be further scaled. As a result, it underscores the need for improvement strategies aimed at increasing production capacity and capturing additional orders to support future growth.

Two actionable strategies were identified for scenario testing: implementing overtime work and outsourcing, as decided by the sample company's management. These strategies aim to expand production capacity through quick wins and cost-effective solutions that avoid significant investments and technical complexities. While conventional methods can provide estimates of the potential outcomes of these strategies, SD techniques offer a more detailed analysis of the entire system and extensive system feedback.

Based on the results of the improved DES model, the current production capacity is approximately 6000 units per month. Outsourcing adds an extra capacity of up to 2000 units per month. Additional units can alternatively be produced during overtime, depending on the number of overtime days in a month. The overtime duration is divided by the optimized throughput time generated by the DES model to determine how many units can be produced within this period. Implementing both improvement strategies at maximum capacity may lead to operational constraints, including storage issues, overproduction, and waste.

5.2.1 SD results

The first scenario for increasing production capacity focuses on testing a single strategy. By utilizing the outsourcing strategy alone, the sample company can achieve the desired production increase, as the outsourcing partner can produce up to 2000 additional units per month. Nonetheless, this approach leaves no allowance for rejected units, as the production output is already at its maximum capacity. Moreover, this strategy proves less profitable because each outsourced unit costs 16% more than the internal operating cost.

With an estimated operating cost of RM180.00 per unit, meeting the additional production demand would require outsourcing 2000 units at a cost of RM208.80 per unit. This results in a total monthly expense of RM417,600, which is RM57,600 higher than the production cost of RM360,000 for producing the same quantity internally. This increased expense would ultimately reduce the company's profit margin.

While using the overtime strategy only, the sample company could produce up to 2198 additional units per month by operating continuously, with two daily shifts of 10.75 hours each over 30 working days, totaling 38,700 minutes of production time. Dividing this total production time by the optimized throughput time of 4.72 minutes per unit, as determined by the DES model, yields a total output of 8198 units per month. After accounting for rejections and downtime, subtracting the 6000 units produced during regular working hours results in a generation of 2000 units' net.

However, operating continuously, including weekends, is impractical for the production department. Sustained strain on resources and personnel could result in diminishing returns, increased fatigue, and a higher likelihood of errors, ultimately making this strategy unsustainable. Additionally, operating costs increase by 7% per unit with this strategy, raising the cost per unit to RM192.60. Multiplying this by 2000 units results in a monthly overtime cost of RM385,200.

In meeting customer demand effectively, the sample company must integrate both strategies. By utilizing overtime and outsourcing, the sample company can balance the production load, preventing overburdening of both the internal workforce and external facilities. The goal is to determine the optimal combination of these strategies to achieve the desired increase in production capacity in a cost-effective and efficient way. To enhance the outcomes, the initial SD model was modified by adding a proportionality variable.

To increase production from 6000 to 7000 units per month, the sample company utilizes 20% of the maximum output from the outsourcing partner and 40% from overtime. For the next increment, reaching 8000 units per month, the sample company relies on 45% outsourcing and 55% overtime. By refining the simulation model, the company determined that producing an additional 2000 units per month would increase operating costs by RM399,780. This approach saves RM17,820 compared to relying solely on the outsourcing strategy.

5.3 Discussion

VSM, a widely used lean manufacturing tool, is effective in identifying non-value-added activities within processes and resolving bottleneck issues [54]. Al-Rifai [55] emphasized that a detailed analysis of manufacturing processes using VSM can yield substantial benefits by overcoming operational challenges through streamlining operations. Chao et al. [56] suggest that the effectiveness of VSM analysis can be further enhanced by integrating computer simulation, as the transformation of existing production processes requires the incorporation of information systems.

This study adopts an approach that combines process flow mapping with DES modeling to diagnose problems within the production process. While many studies rely solely on VSM to identify bottlenecks as the primary source of inefficiencies [57, 58], this study reveals that the bottleneck processes are not the main factor hindering the sample company from achieving its planned production targets. Instead, the simulation analysis uncovers significant delays caused by extended waiting times between production stages, which slow down operations and prolong production processing durations.

Most studies combining VSM with simulation modeling follow an approach that includes developing a current-state map, analyzing the outcomes, and optimizing the process by designing a future state map. Addressing various challenges often requires improvement strategies tailored to specific production environments, considering unique needs, available resources, and minimal investments. The main goal of such studies is to improve the operational performance of existing production processes by minimizing or eliminating waste. This improvement is evaluated by analyzing simulation results and calculating the percentage of achievement, as highlighted by Reda and Dvivedi [59], Mishra et al. [60], and many others.

In this study, parallel production, production leveling, and a combination of both were implemented as improvement strategies to optimize the current production process. Analysis from the scenario testing indicated that production leveling produced the most notable improvements compared to the other approaches. It effectively reduced throughput time and waiting time between production stages. A reduction in delays significantly improved productivity and efficiency, creating the capacity to produce an additional 2000 units. The company also can fully achieve its planned monthly production target of 4000 units, well within the available monthly production time.

Furthermore, the approach used in this study goes beyond a single approach in the process improvement study. By combining DES and SD, this hybrid approach not only focuses on waste reduction and process optimization but also strategically plans for future production capacity increases to meet additional demand. This combination is referred to as a sequential approach, where two or more distinct models are executed in sequence, with the output of one serving as the input for the next model [53]. Real-world problems and manufacturing operations are inherently complex, featuring many variables and characteristics, making it uncommon for a single method to effectively address all of them [52].

This study used optimized parameters from the DES simulation results of the designed future state map as input for the SD model. Scenario testing of the SD model was then analyzed to identify practical strategies for expanding production capacity cost-effectively. While the hybrid simulation approach among scholars remains relatively underrepresented, and the technique of combined simulation methods was unclear [52], this study presents a novel approach. It allows decision-makers to assess different improvement strategies before implementation to tackle modern, complex business challenges.

6. Conclusion

Manufacturing companies are undergoing significant transformations driven by various factors, including increasingly volatile markets, shifting customer demands, shorter product life cycles, and rising complexity. In such a dynamic environment, static production systems are becoming less effective as they struggle to keep up with evolving needs. Moreover, the ongoing digitalization of production plays a crucial role in reshaping operations. These trends highlight the growing need for flexible production systems, which require both short-term adjustments to the value stream and cost-effective long-term strategies.

In conclusion, this study makes a significant contribution to the field of operations management, particularly in enhancing production processes. By combining DES and SD, it introduces an innovative approach for evaluating the effectiveness of various improvement strategies. Academically, the study advances knowledge by demonstrating the practical application of these advanced methods in real-world contexts, bridging the gap between theoretical research and industrial practice. These contributions are invaluable for researchers and practitioners aiming to develop data-driven, scalable solutions for production process improvement.

Moreover, the use of computer simulation techniques in this study allowed the company to assess the potential impacts of proposed strategies in a controlled, risk-free environment. This approach facilitated detailed scenario analysis, enabling comparisons of different strategies under varying conditions. As a result, the sample company identified and implemented methods specifically suited to its operational needs and business priorities. The insights derived from these simulations supported informed decision-making, reducing reliance on costly trial-and-error methods in real-world operations.

Acknowledgements

The authors extend their heartfelt gratitude to University Malaysia Pahang Al-Sultan Abdullah (UMPSA) for their invaluable financial support under Grant No. RDU230321. The grant provided critical resources and opportunities that have significantly contributed to the outcomes of this study.

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References

[1] Alves JRX, Alves JM. Production management model integrating the principles of lean manufacturing and sustainability supported by the cultural transformation of a company. International Journal of Production Research. 2015;**53**(17):5320-5333. DOI: 10.1080/00207543.2015.1033032

[2] Singh J, Singh H. Continuous improvement philosophy—Literature review and directions. Benchmarking: An International Journal. 2015;**22**(1):75-119. DOI: 10.1108/BIJ-06-2012-0038

[3] Roman DJ, Osinski M, Erdmann RH. A substantive theory on the implementation process of operational performance improvement methods. Revista de Administração. 2017;**52**(2):148-162. DOI: 10.1016/j.rausp.2016.12.005

[4] Andersson C, Bellgran M. On the complexity of using performance measures: Enhancing sustained production improvement capability by combining OEE and productivity. Journal of Manufacturing Systems. 2017;**35**:144-154. DOI: 10.1016/j.jmsy.2014.12.003

[5] Alexander P, Antony J, Rodgers B. Lean six sigma for small and medium sized manufacturing enterprises: A systematic review. International Journal of Quality & Reliability Management. 2019;**36**(3):378-397. DOI: 10.1108/IJQRM-03-2018-0074

[6] Aqlan F, Al-Fandi L. Prioritizing process improvement initiatives in manufacturing environments. International Journal of Production Economics. 2018;**196**:261-268. DOI: 10.1016/j.ijpe.2017.12.004

[7] Zighan S, Ruel S. SMEs' resilience from continuous improvement lenses. Journal of Entrepreneurship in Emerging Economies. 2023;**15**(2):233-253. DOI: 10.1108/JEEE-06-2021-0235

[8] Malinova M, Gross S, Mendling J. A study into the contingencies of process improvement methods. Information Systems. 2022;**104**:101880. DOI: 10.1016/j.is.2021.101880

[9] Samaranayake P, McLean MW, Weerabahu SK. Application of lean and quality improvement methods for improving operational performance in coal supply chains: A case study. International Journal of Quality & Reliability Management. 2024;**41**(6):1594-1622. DOI: 10.1108/IJQRM-04-2023-0138

[10] Mulugeta L. Productivity improvement through lean manufacturing tools in Ethiopian garment manufacturing company. Materials Today Proceedings. 2021;**2020**(37):1432-1436. DOI: 10.1016/j.matpr.2020.06.599

[11] Lacerda AP, Xambre AR, Alvelos HM. Applying value stream mapping to eliminate waste: A case study of an original equipment manufacturer for the automotive industry. International Journal of Production Research. 2016;**54**(6):1708-1720. DOI: 10.1080/00207543.2015.1055349

[12] Vo B, Kongar E, Suárez-Barraza MF. Kaizen event approach: A case study in the packaging industry. International Journal of Productivity and Performance Management. 2019;**68**(7):1343-1372. DOI: 10.1108/IJPPM-07-2018-0282

[13] Abeygunasekera AWJC, Bandara W, Wynn MT, Yigitbasioglu O. How to make it stick? Institutionalising

process improvement initiatives. Business Process Management Journal. 2022;**28**(3):807-833. DOI: 10.1108/BPMJ-03-2021-0170

[14] Kashfi H, Aliee FS. Business process improvement challenges: A systematic literature review. In: 11th International Conference on Information and Knowledge Technology. 2020. pp. 122-126

[15] Antony J, Gupta S. Top ten reasons for process improvement project failures. International Journal of Lean Six Sigma. 2019;**10**(1):367-374. DOI: 10.1108/IJLSS-11-2017-0130

[16] Rashid OA, Ahmad MN. Business process improvement methodologies: An overview. Journal of Information System Research Innovation. 2013;**5**:45-53

[17] Psomas E, Antony J. Research gaps in lean manufacturing: A systematic literature review. International Journal of Quality & Reliability Management. 2019;**36**(5):815-839. DOI: 10.1108/IJQRM-12-2017-0260

[18] Ghatorha KS, Sharma R, Singh G. Application of root cause analysis to increase material removal rate for productivity improvement: A case study of the press manufacturing industry. Materials Today Proceedings. 2019;**26**:1780-1783. DOI: 10.1016/j.matpr.2020.02.374

[19] Khan SA, Kaviani MA, Galli B, Ishtiaq P. Application of continuous improvement techniques to improve organization performance: A case study. International Journal of Lean Six Sigma. 2019;**10**(2):542-565. DOI: 10.1108/IJLSS-05-2017-0048

[20] Memari A, Panjehfouladgaran HR, Abdul Rahim AR, Ahmad R. The impact of lean production on operational performance: A case study. Asia-Pacific Journal of Business Administration. 2022. DOI: 10.1108/APJBA-04-2022-0190

[21] Ciano MP, Dallasega P, Orzes G, Rossi T. One-to-one relationships between Industry 4.0 technologies and lean production techniques: A multiple case study. International Journal of Production Research. 2021;**59**(5):1386-1410. DOI: 10.1080/00207543.2020.1821119

[22] Cocca P, Marciano F, Alberti M, Schiavini D. Leanness measurement methods in manufacturing organisations: A systematic review. International Journal of Production Research. 2019;**57**(15-16):5103-5118. DOI: 10.1080/00207543.2018.1521016

[23] Dadashnejad AA, Valmohammadi C. Investigating the effect of value stream mapping on operational losses: A case study. Journal of Engineering, Design and Technology. 2018;**16**(3):478-500. DOI: 10.1108/JEDT-11-2017-0123

[24] Lucato WC, Calarge FA, Junior ML, Calado RD. Performance evaluation of lean manufacturing implementation in Brazil. International Journal of Productivity and Performance Management. 2014;**63**(5):529-549. DOI: 10.1108/IJPPM-04-2013-0085

[25] Belekoukias I, Garza-Reyes JA, Kumar V. The impact of lean methods and tools on the operational performance of manufacturing organisations. International Journal of Production Research. 2014;**52**(18):5346-5366. DOI: 10.1080/00207543.2014.903348

[26] Jasti NVK, Kodali R. Lean production: Literature review and trends. International Journal of Production Research. 2015;**53**(3):867-885. DOI: 10.1080/00207543.2014.937508

[27] Pacheco DA, de Pergher I, Antunes-Junior JAV, Roehe-Vaccaro GL. Exploring the integration between lean and the theory of constraints in operations management. International Journal of Lean Six Sigma. 2019;**10**(3):718-742. DOI: 10.1108/IJLSS-08-2017-0095

[28] Marodin GA, Saurin TA. Implementing lean production systems: Research areas and opportunities for future studies. International Journal of Production Research. 2013;**51**(22):6663-6680. DOI: 10.1080/00207543.2013.826831

[29] Helleno AL, Pimentel CA, Ferro R, Santos PF, Oliveira MC, Simon AT. Integrating value stream mapping and discrete events simulation as decision making tools in operation management. International Journal of Advanced Manufacturing Technology. 2015;**80**:1059-1066. DOI: 10.1007/s00170-015-7087-1

[30] Cortes H, Daaboul J, Duigou JL, Eynard B. Strategic lean management: Integration of operational performance indicators for strategic lean management. IFAC-PapersOnLine. 2016;**49**(12):65-70. DOI: 10.1016/j.ifacol.2016.07.551

[31] Irani SA, Zhou J. Value stream mapping of a complete product. In: White Paper of Lean Manufacturing Japan (Issue 1). 2011

[32] Lugert A, Völker K, Winkler H. Dynamization of value stream management by technical and managerial approach. Procedia CIRP. 2018;**72**(March):701-706. DOI: 10.1016/j.procir.2018.03.284

[33] Netland TH, Schloetzer JD, Ferdows K. Implementing corporate lean programs: The effect of management control practices. Journal of Operations Management. 2015;**36**:90-102. DOI: 10.1016/j.jom.2015.03.005

[34] Sharma P. Discrete event simulation. International Journal of Scientific and Technology Research. 2015;**4**(04):136-140. DOI: 10.1145/317500.317518

[35] Buer SV, Semini M, Ola SJ, Sgarbossa F. The complementary effect of lean manufacturing and digitalisation on operational performance. International Journal of Production Research. 2021;**59**(7):1976-1992. DOI: 10.1080/00207543.2020.1790684

[36] Yang T, Kuo Y, Su C-T, Hou C-L. Lean production system design for fishing net manufacturing using lean principles and simulation optimization. Journal of Manufacturing Systems. 2015;**34**:66-73. DOI: 10.1016/j.jmsy.2014.11.010

[37] Abdulmalek FA, Rajgopal J. Analyzing the benefits of lean manufacturing and value stream mapping via simulation: A process sector case study. International Journal of Production Economics. 2007;**107**:223-236. DOI: 10.1016/j.ijpe. 2006.09.009

[38] Abideen AZ, Mohamad FB, Fernando Y. Lean simulations in production and operations management—A systematic literature review and bibliometric analysis. Journal of Modelling in Management. 2020;**16**(2):623-650. DOI: 10.1108/JM2-05-2019-0103

[39] Bowles DE, Gardiner LR. Supporting process improvements with process mapping and system dynamics. International Journal of Productivity and Performance Management. 2018;**67**(8):1255-1270. DOI: 10.1108/IJPPM-03-2017-0067

[40] Bait S, Di Pietro A, Schiraldi MM. Waste reduction in production processes through simulation and VSM. Sustainability. 2020;**12**(8):1-14. DOI: 10.3390/SU12083291

[41] Schmidtke D, Heiser U, Hinrichsen O. A simulation-enhanced value stream mapping approach for optimisation of complex production environments. International Journal of Production Research. 2014;**52**(20):6146-6160. DOI: 10.1080/00207543.2014.917770

[42] Omogbai O, Salonitis K. Manufacturing system lean improvement design using discrete event simulation. Procedia CIRP. 2016;**57**:195-200. DOI: 10.1016/j.procir.2016.11.034

[43] Mohd Yusoof MY, Nik Mohamed NMZ, Nelfiyanti, Md Yasir ASH. Assessment of man and method toward the assembly line improvement in automotive manufacturing. Journal of Modern Manufacturing Systems and Technology. 2023;**7**(1):7-14. DOI: 10.15282/jmmst.v7i1.9017

[44] Uriarte AG, Ng AHC, Zuñiga ER, Moris MU. Improving the material flow of a manufacturing company via lean, simulation and optimization. In: International Conference on Industrial Engineering and Engineering Management. 2018. pp. 1245-1250. DOI: 10.1109/IEEM.2017.8290092

[45] Georgiadis P. An integrated system dynamics model for strategic capacity planning in closed-loop recycling networks: A dynamic analysis for the paper industry. Simulation Modelling Practice and Theory. 2013;**32**:116-137. DOI: 10.1016/j.simpat.2012.11.009

[46] Mendoza JD, Mula J, Campuzano-Bolarin F. Using systems dynamics to evaluate the tradeoff among supply chain aggregate production planning policies. International Journal of Operations & Production Management. 2014;**34**(8):1055-1079. DOI: 10.1108/IJOPM-06-2012-0238

[47] Deif AM, El-Maraghy H. Cost performance dynamics in lean production leveling. Journal of Manufacturing Systems. 2014;**33**:613-623. DOI: 10.1016/j.jmsy. 2014.05.010

[48] Wang Z, Ng TS, Ee WLA. A system dynamics model for industrial symbiosis capacity formation. Journal of Simulation. 2021;**17**(4):381-406. DOI: 10.1080/17477778.2021.2007807

[49] Suryani E, Dewi LP, Junaedi L, Hendrawan RA. A model to improve corn productivity and production. Journal of Modelling in Management. 2020;**15**(2):589-621. DOI: 10.1108/JM2-11-2018-0181

[50] Filho MG, Uzsoy R. The impact of simultaneous continuous improvement in setup time and repair time on manufacturing cycle times under uncertain conditions. International Journal of Production Research. 2013;**51**(2):447-464. DOI: 10.1080/00207543.2011.652261

[51] Nicholds BA, Mo JPT. Estimating performance from capabilities in business process improvement. Business Process Management Journal. 2016;**22**(6):1099-1117. DOI: 10.1108/BPMJ-09-2015-0129

[52] Brailsford SC, Eldabi T, Kunc M, Mustafee N, Osorio AF. Hybrid simulation modelling in operational research: A state-of-the-art review. European Journal of Operational Research. 2019;**278**(3):721-737. DOI: 10.1016/j.ejor.2018.10.025

[53] Morgan JS, Howick S, Belton V. A toolkit of designs for mixing discrete event simulation and system dynamics. European Journal of Operational Research. 2017;**257**(3):907-918. DOI: 10.1016/j.ejor.2016.08.016

[54] Palange A, Dhatrak P. Lean manufacturing a vital tool to enhance productivity in manufacturing. Materials Today Proceedings. 2021;**46**:729-736. DOI: 10.1016/j.matpr.2020.12.193

[55] Al-Rifai M. Mapping the path to efficiency: Harnessing value stream mapping (VSM) and lean tools for streamlined electronic device manufacturing. Measuring Business Excellence. 2024;**28**(3):396-414. DOI: 10.1108/MBE-06-2024-0087

[56] Chao B, Zhang C, Zhang Y, Guo H, Ren Y, Zhang H. Research on optimization and simulation of sand casting production line based on VSM. International Journal of Lean Six Sigma. 2022;**13**(6):1185-1199. DOI: 10.1108/IJLSS-10-2021-0183

[57] Hussain D, Figueiredo MC. Improving the time-based performance of the preparatory stage in textile manufacturing process with value stream mapping. Business Process Management Journal. 2023;**29**(3):801-837. DOI: 10.1108/BPMJ-08-2022-0366

[58] Sangwa NR, Sangwan KS. Leanness assessment of a complex assembly line using integrated value stream mapping: A case study. TQM Journal. 2023;**35**(4):893-923. DOI: 10.1108/TQM-12-2021-0369

[59] Reda H, Dvivedi A. Application of value stream mapping (VSM) in low-level technology organizations: A case study. International Journal of Productivity and Performance Management. 2022;**71**(6):2393-2409. DOI: 10.1108/IJPPM-03-2021-0118

[60] Mishra AK, Sharma A, Sachdeo M, Jayakrishna K. Development of sustainable value stream mapping (SVSM) for unit part manufacturing: A simulation approach. International Journal of Lean Six Sigma. 2020;**11**(3):493-514. DOI: 10.1108/IJLSS-04-2018-0036