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Exploring Lean Manufacturing Integration and Performance Evaluation for Process Optimization in the Food Processing Industry

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Abstract
Lean manufacturing has proven effective across many industries, yet its application in food processing remains constrained by product perishability and process variability. This study develops a hybrid Lean–Simulation framework that integrates Gemba walks, check sheets, Pareto analysis, Fishbone diagrams, and Value Stream Mapping (VSM) with Monte Carlo simulation to capture both deterministic inefficiencies and stochastic variability. Results show an average processing time of 354.98 minutes, with the 95th percentile at 378.96 minutes, confirming that Thawing and Packing are the dominant bottlenecks. By incorporating probabilistic analysis, the framework extends beyond conventional Lean tools and provides managers with actionable insights to enhance stability, allocate resources strategically, and improve responsiveness in food processing operations.

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1. Introduction

The food processing industry plays a critical role within the worldwide agri-food value chain, transforming raw agricultural inputs into edible products and linking primary production with end-user markets (Skalkos, 2023). It not only contributes significantly to economic development and employment (Miranda et al., 2023) but also plays a critical role in ensuring food quality, safety, and availability (Wang et al. 2024; Dhal and Kar, 2025). As global demand for processed food rises due to urbanization (Ruel et al., 2017), population growth (Daszkiewicz, 2022), and shifting dietary preferences (Ilieva et al., 2025), food manufacturers face increasing pressure to deliver high volumes of standardized products while maintaining cost-efficiency and regulatory compliance (Dziuba and Szczyrba, 2023; Szczyrba and Szataniak, 2024).

In response to the increasing challenges posed by climate change and the scarcity of natural resources, both academics and industry have been researching approaches and practices to improve environmental and resource management. As manufacturing systems consume large amounts of energy and raw materials, there is an increasing expectation that they will correspond with global sustainability standards (Glavič, 2021; Al-dalain et al., 2024). In response, Lean production methods have gained widespread recognition not merely as a cost-reduction strategy, but as a strategic enabler of resource efficiency positioning Lean as a foundational element in advancing circular economy principles and enhancing sustainable manufacturing performance (Sasso et al. 2025; ALShanti et al., 2025). Lean offers a pathway to more sustainable industrial operations by reducing waste and optimizing value (Hossain et al. 2024), especially in industries with high levels of uncertainty and resource sensitivity (Parveen and Rao 2009; Lalremruati and Khanna 2023; Mogotsi and Saruchera 2023; Ocieczek et al., 2025).

The core principles of lean management emphasize continuous improvement (Martínez Sanahuja 2020) respect for people (Barros et al. 2024), and the elimination of non-value-added activities (Sudhakara et al., 2020). These concepts have significantly improved operational performance in a variety of industries, including electronics (Mathiyazhagan et al., 2022), healthcare (Mahmoud et al. 2021), automotive (Aripin et al. 2024), and aerospace (Liu et al., 2024). Nevertheless, the effective implementation of lean practices remains contextual and is often constrained by social, organizational, technical, and cultural and social barriers (Pedrosa et al., 2023; De Silva et al., 2025; Villena and Vargas, 2025).

The food processing industry presents distinctive challenges for Lean implementation. Unlike many manufacturing sectors, it must simultaneously guarantee stringent food safety standards (Bravo-Paliz and Avilés-Sacoto, 2023), manage the rapid deterioration of perishable products (Carbajal-Vásquez et al., 2023), and respond to highly variable consumer demand (Kapsdorferová et al., 2024; Songkhwan et al.2025). These conditions introduce levels of uncertainty and variability that conventional Lean techniques, which are largely designed for more stable production environments, may not adequately address. As a result, Lean adoption in food processing often yields inconsistent outcomes and limited sustainability gains. While earlier studies have acknowledged the potential of Lean practices to improve efficiency in food operations, most remain conceptual or narrowly focused, with few offering structured frameworks that explicitly integrate theoretical insights with operational tools tailored to the realities of food production systems.

This study developed an uncertainty aware Lean framework that combines deterministic root cause analysis (Fishbone diagrams, Pareto charts,VSM) with stochastic process simulation to enable more robust waste reduction strategy evaluation in environments with high operational variability. The framework is applied as a case study in a frozen food production line characterized by six sequential processing stages exhibiting wide ranging process reliability and significant change over time variability, providing an empirically rich context for examining how probabilistic analysis complement deterministic lean tools.

To systematically evaluate the complementary value of integrating Lean analysis with probabilistic simulation, this study addresses three specific research questions: First, what are the primary sources and magnitudes of process variability contributing to total lean time variation in multi stage production systems? Second, how does probabilistic analysis (Monte Carlo Simulation) enhance decision making compared to deterministic value stream mapping in identifying waste reduction opportunities? And third, to what extent is total lead time sensitive to changeover time reductions versus uptime improvements across different production stages?

This study contributes to the operation management by addressing a critical gap in Lean management research the lack of structured, uncertainty- aware analytical approach that integrate deterministic lean tools with stochastic simulation. It advances theory by showing how Monte Carlo based modeling overcomes the limitations of traditional Lean and Value Stream Mapping analysis, enabling quantification of variability, and prediction of system behavior under uncertainty. The following section discusses the literature review, followed by an explanation of the research methodology and experimental procedures. Finally, the paper presents the conclusions, including limitations and suggestions for future research.

2. Literature review

Throughout the years, numerous authors have presented various definitions of lean manufacturing in the literature that focus on eliminating waste, adding value, and improving overall organizational performance (Dilanthi, 2015; Henao and Sarache, 2023). One widely recognized definition is the one presented by (Shah and Ward ,2007) "Lean production is an integrated socio-technical system whose main objective is to eliminate waste by concurrently reducing or minimizing supplier, customer, and internal variability".

Lean manufacturing principles, originally developed within the automotive sector (Nordin et al., 2014), have since been widely adopted across various industries to enhance operational efficiency and eliminate waste. In the automotive industry, (Rifqi et al., 2021) conducted a case study employing the DMAIC (Define, Measure, Analyze, Improve, Control) framework in an automotive manufacturing setting. The study demonstrated significant improvements in production planning, material flow, and financial outcomes, reinforcing the efficacy of lean tools in high-volume manufacturing environments. (Sekhar et al., 2023) used a machine learning approach to develop an effective lean manufacturing soft sensor that classified auto manufacturers into high, medium, or low levels of lean manufacturing according to their production flexibility. More recently, (Aripin et al., 2024) adopts a qualitative methodology, collecting primary data through in-depth interviews and purposeful sampling. The criteria for participating organizations and informants are designed to ensure greater insights into lean manufacturing. The authors list a number of crucial elements for maintaining Lean Manufacturing, such as supplier management, internal collaboration, culture, effective leadership, technology integration, resource management, and knowledge management.

Beyond manufacturing, lean methodology has also been adapted to service-oriented sectors such as healthcare. (Talero-Sarmiento et al., 2024) explored the implementation of Lean strategies in healthcare through a concept-centric review of 44 studies on Lean healthcare. The review showed that the lean approaches dramatically enhanced patient outcomes, operational performance, and cost-effectiveness. The authors also highlighted the challenges including resistance to change, the complexity of the application, and the sustainability of the implemented strategies. (Veres et al., 2025) discussed the importance of leadership in ensuring effective Lean implementation using a mixed-method approach combining literature review and quantitative data from different public and private healthcare institutions. The findings demonstrate the importance of leadership involvement as well as tailored training in overcoming resistance and driving continual improvement. In addition, Lean concepts have been applied in the technology and electronics manufacturing industry (Manavalan and Jayakrishna, 2019), with a focus on supply chain efficiency and quick product development cycles (Mathiyazhagan et al., 2022). In agriculture sector, (Cuer et al., 2025) applied Lean Production principles to reduce waste on a family farm growing lettuce. Using tools like Value Stream Mapping and the Ishikawa diagram, they identified excessive movement and over-fertilization as key wastes. Their interventions led to a 45% reduction in non-value-adding cycle time, showing that Lean can effectively improve efficiency in small-scale agriculture. Moreover, studies in the ceramics industry evaluated 5S implementation through surveys and expert interviews, revealing that adoption is shaped largely by organizational culture and employee involvement (Kleszcz, 2017).

The food processing industry has increasingly adopted Lean Manufacturing (LM) as a strategy to reduce waste, and ensure sustainable.)Matindana and Shoshiwa ,2025) used Exploratory Factor Analysis and Confirmatory Composite Analysis on data from 113 small and medium enterprises (SMEs) to examine the impact of Lean techniques in Tanzania's food and beverage sector. The study identified lean tools, processes, and outputs as key dimensions of successful implementation, with communication and training also playing vital roles. (Psomas and Deliou 2024) investigated Greek food manufacturing companies to assess how Lean Manufacturing (LM) practices and Industry 4.0 (I4.0) technologies are implemented. Based on a 102 sample of Greek food manufacturing companies, the study found a high adoption of lean manufacturing practices but a low to medium use of I4.0 technologies. However, regression analysis revealed a significant positive impact of I4.0 on enhancing lean manufacturing efforts. (Garcia-Garcia et al., 2022) investigated the effectiveness of lean principles in enhancing operational efficiency and sustainability in food manufacturing. The authors conducted a case study in a Food Factory in UK, to reduce waste during changeover processes. By applying the Single Minute Exchange of Dies (SMED) methodology and optimizing line hopping, the company achieved a 30% reduction in changeover time, Overall Equipment Effectiveness increase to over 70%, and labor costs reduced by 10%.

Several studies have illustrated the significance of incorporating simulation into Lean-oriented process analysis, especially for capturing unpredictability and facilitating managerial decision-making. Monte Carlo simulation has been applied to quantify total lead time as a probability distribution, allowing sensitivity analyses and "what-if" scenarios to evaluate investments and process improvements (Eberle et al. 2014). Other contributions have explored co-simulation frameworks to assess the responsiveness of Lean techniques under conditions of market fluctuation, demand diversification, and resource uncertainty, showing that while some methods (e.g., 5S, Poka Yoke) are universally applicable, others (e.g., Pull, SMED, Cross-training) exhibit strong context dependence (Possik et al., 2022). Moreover, Lean simulation models have been integrated with Discrete Event Simulation (DES) to identify and alleviate delays, queues, and non-value-added operations in supply chains, resulting in substantial reductions in lead time and enhancements in value-added time(Abideen 2024) . More recently, stochastic extensions of Value Stream Mapping (VSM) with Monte Carlo simulation have been proposed to generate more realistic lead-time estimates, enabling more assertive planning and revealing improvement opportunities that deterministic approaches often overlook (Luz et al., 2022).

Lean manufacturing methodologies have been widely applied to identify non-added value and minimize waste in manufacturing; however their application in the food processing sector is limited. The existing research relies mostly on static techniques, with lack of consideration for unpredictability and uncertainty in real-world production contexts. The proposed study addresses these gaps by introducing a novel hybrid method integrating lean manufacturing methods (such as Pareto analysis and VSM) with Monte Carlo simulation to take into account for variability and uncertainty in food processing activities and assess their impact on total lead time. By combining traditional Lean analysis with probabilistic modeling, the framework generates more realistic estimates of lead time and enables risk-aware decision-making. By expanding Lean analysis into the probabilistic field, the work makes a methodological contribution. It also makes a practical contribution by giving food processing manager's useful insights to improve responsiveness, stability, and efficiency.

3. Methodology/Experimental Procedure

This study adopts a structured Lean manufacturing approach tailored to the food processing industry, aiming to identify and eliminate inefficiencies while enhancing operational performance. The procedure combined direct shop-floor observations with analytical tools to identify inefficiencies, prioritize root causes, and model system performance under uncertainty. The methodology comprised six steps, outlined below:

1. Gemba Walk and Data Collection: Observations were conducted over 6 consecutive production days across 2 regular shifts per day, ensuring coverage of time and operator-related variability. A total of 148 process cycles were recorded, a sample size large enough to achieve statistical reliability while remaining feasible for detailed recording. The cycles covered the full process chain, thus ensuring comprehensive representation of production activities. Then, Check sheets were used to record waste occurrences, delays, and deviations.

2. Pareto Analysis The observed inefficiencies were ranked according to frequency and impact to identify the critical few issues.

3. Cause-and-Effect (Fishbone) Diagram: Root causes were categorized into manpower, machines, methods, materials, and environment.

4. Value Stream Mapping (VSM): A detailed map was constructed, capturing average cycle times, waiting times, and lead times based on Z recorded cycles.

5. Monte Carlo Simulation: Based on the process time data taken from the VSM, a Monte Carlo simulation was included into the analysis to measure variability and evaluate operational uncertainty. Each major process stage is modeled using a normal distribution for its respective cycle time. The simulation is run 10,000 iterations, this number of iterations is consistent thresholds documented in prior applied simulation research (Chesalin et al., 2022), generating a probabilistic profile of the system's performance. This approach provides a dynamic understanding of production behaviour under uncertainty, moving beyond static metrics to inform more resilient and data-driven decision-making.

3.1. Implementation of Gemba walks

The first stage involved conducting a Gemba walk to observe production activities directly, identify sources of waste and inefficiency, and uncover potential improvement opportunities. The initial walk was scheduled during peak operating hours, with prior notice given to staff to ensure transparency and cooperation. This preliminary visit aimed to verify that operational processes aligned with standard procedures and yielded the expected outcomes. It also served to build rapport and trust with shop-floor employees through direct, face-to-face engagement. Subsequent Gemba walks and informal consultations with operators revealed a number of recurring inefficiencies and process-related issues. The following were among the most frequently observed or reported:

- Excessive material removal during the portioning process.
- Underutilization of the tamping machine and thawing room.
- The compressing machine requires a 25-minute cleaning cycle prior to each batch.
- Manual forklifts are not fully utilized.
- Raw material pallets are frequently relocated within the thawing area.
- Local distribution vans are not being used to their full capacity.
- Compressing machine operators wasted time walking around to check settings, communicate, and monitor other processes.
- Frequent miscommunication between operators led to production delays.

3.2. Check sheet

After identifying the main defects and waste, check sheets were designed to collect the defect rate for further analysis. Check sheet is considered as the simplest quality control tool, where cross reference tables are used to record occurrences of defects and collect data. In the presented research, check sheets were developed to collect the rate of occurrence of different types of defects on the production line. Data was collected and used for further analysis on the next stages.

3.3. Pareto Analysis and Fishbone Diagram

Pareto analysis was conducted to determine the potential sources of waste and defects in the production process of frozen foods. Pareto analysis is a technique that was originally developed by Vilfredo Pareto (1848 - 1923) and used for decision making by identifying and selecting the factors with the most significant overall effect. The technique is based on identifying that 80% of the effects come from 20% of causes (Karuppusami and Gandhinathan, 2006; Denning, 2012). Therefore, in this stage we used Pareto analysis to identify and prioritize the actions and process that contribute the most to waste. Figure 1 shows a Pareto analysis of waste categories, ranking them by frequency of occurrence. The trend line illustrates the cumulative percentage of defects. The results indicate that 80% of rejections are reached in the fourth waste. The graph indicates that excess stock of raw food awaiting processing accounts for approximately 22% of total waste, while frequent miscommunication between operators contributes around 20%. Additionally, the frequent relocation of raw material pallets within the thawing area represents 18% of waste and the requirement for a 25-minute cleaning cycle of the tamping machine before each batch contributes 14.4%.

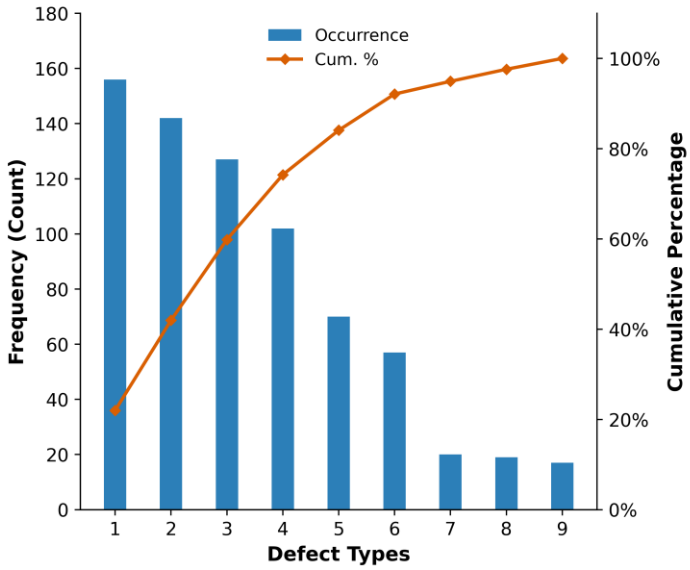

Fig. 1. Pareto chart for Production process defects

The primary contributors to operational inefficiency are categorized by frequency (bars) and their cumulative impact (line). The numbered identifiers on the horizontal axis correspond to the following waste and defect types: (1) excess stock of raw food awaiting processing; (2) frequent miscommunication between operators leading to production delays; (3) frequent relocation of raw material pallets within the defrosting area; (4) a 25-mintue cleaning cycle required for the tamping machine prior to each batch; (5) underutilization of the tamping machine and defrosting room; (6) incomplete utilization of manual forklifts; (7) excessive material removal during the trimming process; (8) significant weight loss of materials post-defrosting; and (9) time wasted by tamping machine operators walking to check settings and other processes.

A Cause-and-effect analysis (also known as Ishikawa Diagram) was used to verify all the possible contributing causes of the waste that resulted from Pareto Analysis and check sheets. The reasons for defects and wastes in production lines and trim lines can be easily determined using the cause effect analysis tool. The cause-and-effect diagram for the selected defects is shown in Figure 1. The horizontal arrow is used to indicate the effect. Meanwhile, the main causes are indicated by arrows pointing in the direction of the horizontal arrows touching the relevant cause.

To develop a cause effect diagram, a series of meetings and discussions were conducted with the managers, supervisors and staff of the factory to identify the main causes of the aforementioned wastes and defects. The cause of defects and waste were grouped into five main categories as shown in Figure (2): Man, Technology, Machine, Environment, and Method. The analysis highlights that the dominant contributors are lack of predictive maintenance and underutilized machines, reliance on outdated technology and manual operations, insufficiently trained employees and resistance to new technology, poorly designed production flows with inadequate planning, and weak standardization coupled with poor inventory management.

Defects Temperature fluctuations Congested defrosting area Excess raw food stock to long holding time Environment Method Cleaning not synchronized with production schedule Excessive material removal during trimming process Frequent allocation of pallet in defrosting room High moisture variation after thawing Inconsistent batch size Uncontrolled defrosting temperature Material Machine Manpower Thawing machine requires 25- minutes cleaning cycle. Underutilization of compressing machine Long walking distance due to poor layout Inadequate machine setup training Shift handover communication gaps.

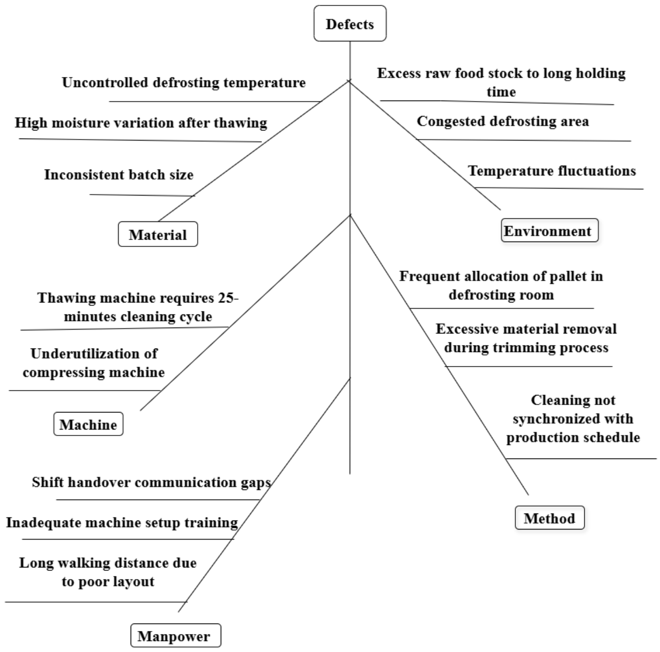

Fig. 2. Fishbone Diagram.

3.4. Value Stream Mapping

To evaluate how the root causes identified in the Fishbone diagram influence the overall production performance, a Value Stream Map (VSM) (Figure 3) was developed. The process begins with Thawing, which takes approximately 85 minutes of cycle time and an additional 42 minutes for changeovers, operating at a low 11% uptime, indicating substantial inefficiencies. Next, materials proceed to Marinating, with a 20-minute cycle time, 14-minute changeover, and an uptime of 70%, still reflecting limited operational effectiveness. The Compressing stage follows, requiring 25 minutes per cycle, 22 minutes for changeovers, and achieving 80% uptime. In the Portioning (Trimming) process, performance improves, with a 55-minute cycle, 11-minute changeover, and a 90% uptime, marking a relatively stable operation. The Shock Freeze stage is more efficient, with a 95-minute cycle, 9-minute changeover, and 95% uptime. Finally, in Packing, the process takes 85 minutes per cycle, 8 minutes for changeovers, and operates at 94% uptime before products are shipped. Overall, the VSM highlights Thawing and Packing as the most significant contributors to total lead time and variability.

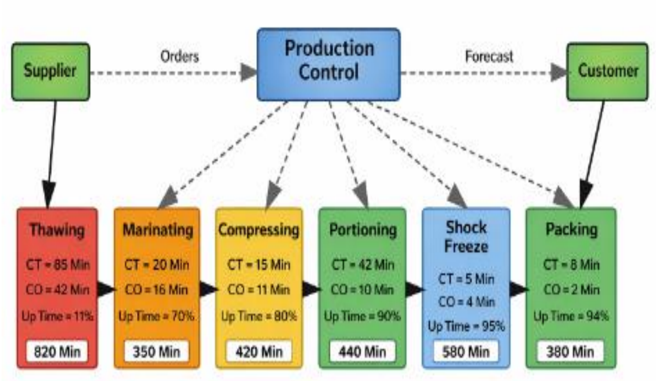

Fig. 3. Value stream Mapping

Table (1) illustrates the quantitative performance measures derived the Value Stream Map, offering a comparative analysis of process level efficiency across throughout the six production stages. The table illustrate the cycle time, changeover time the up-time percentage, and Takt time.The data reveal substantial performance heterogeneity, with up time ranging from a critically low 11% in Thawing to operationally mature levels of 94-95% in Shock Freeze and Packing. The weighted average up-time of 73% across all stages masks the severity of the Thawing bottleneck, which operates at only 11% effective availability, implying 89% downtime that cascades delays throughout the entire value stream. These metrics quantitatively support prioritizing reliability centered maintenance and process stabilization interventions in the Thawing stage to achieve maximum system wide impact.

Table 1. Summary of operational parameters for each process stage

Process Stage	Cycle Time (min)	Changeover time (min)	Up-Time (%)	Takt Time	Bottelneck
Thawing	85	42	11	820	Critical
Marinating	20	14	70	350	NO
Compress-ing	25	22	80	420	NO
Portioning (Trimming)	55	11	90	440	NO
Shock Freeze	95	9	95	580	Secondary
Packing	85	8	94	380	NO

3.5. Monte Carlo Simulation

To support the analysis of the data, we applied Monte Carlo Simulation to provide a probabilistic understanding of process presented, in addition to what static Lean tools can offer. It was employed to account for the unpredictability and fluctuation in the food processing system's overall lead time. Each stage of the production was modeled as a random variable following a normal distribution. The Monte Carlo Simulation results for one unit, conducted separately for each department using a normal distribution. For each simulation run, CT and CO were randomly sampled from a normal distribution with 10% variability. Figure 4 illustrates the simulation generated statistical measures; mean, standard deviation and minimum and maximum for each process.

The results show that the average processing time was 354.98 minutes, with a standard deviation of 24.61 minutes. The 95th percentile value was 378.96 minutes, which indicates that the total output time will stay below this barrier under 95% of operating situations. These results provide a probabilistic insight on the variability found in food processing systems, instead of providing a single-point estimate as in traditional lean techniques. As the results indicate the Thawing and Packing processes are the most contributors to the total processing time.

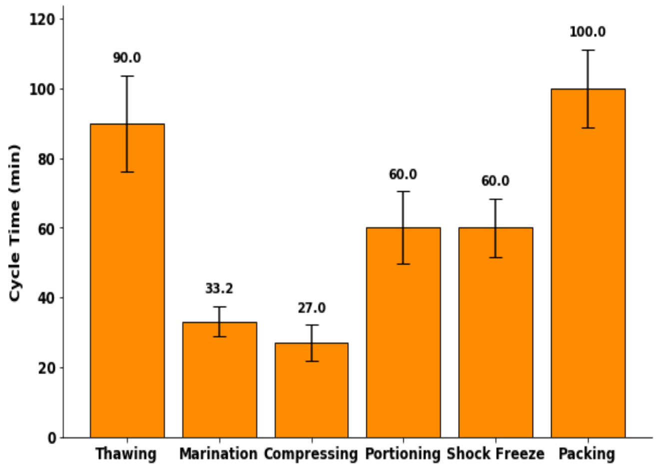

Fig. 4. Monte Carlo Simulation results

From a decision-making perspective, Thawing and Packing emerge as critical leverage points for Kaizen implementation, as they account for the largest share of total processing delays in the system. Targeted Kaizen activities at these stages could focus on reducing changeover times, stabilizing uptime, and minimizing cycle time variability. While this study did not implement Kaizen events directly, the hybrid Lean–Simulation framework provides a clear baseline for prioritization. For example, managers could track potential improvements in cycle time reduction (e.g., Thawing from 85 minutes toward industry benchmarks), changeover efficiency (e.g., lowering Packing changeovers from 8 minutes to 5), and system predictability (narrowing standard deviation in total processing time). By linking Kaizen opportunities to quantified process inefficiencies, the framework offers actionable directions for continuous improvement, even before direct implementation of KPIs.

3.6. Simulation Model and Assumptions

The Monte Carlo Simulation was executed in Python 3.13.5 using standard scientific libraries, conducting 10,000 iterations to represent the six stage serial manufacturing cycle (Thawing → Marinating → Compressing → Portioning → Shock Freeze → Packing) under batch processing logic. Each batch advance sequentially through all stages without splitting. Cycle time and Changeover time for each stage were modeled using normal distribution whose mean and standard deviation were estimated and observed shop-floor samples and cross-checked with supervisor logs. Normal distribution were chosen because individual processing time are composites of numerous independent sub operation, hence they are conceptually consistent with the Central Limit Theorem. The model makes the following assumptions: limitless queue capacity (no blocking), FIFO discipline, independent sampling of Cycle time and Changeover time across stages. Time study measurements, operator interviews, and average obtained from VSM were all used as parameter sources.

Sensitivity Analysis

In this section, we illustrate the impact of changing the changeover time for each process on the total lead time. Figure 5 illustrates the impact range (in minutes) of changing a certain process's changeover time by ± 5%, ± 10%, and ± 20%. The bar's length indicates the overall change in minutes between the increased and decreased times; for example, the base time for the thawing process is 40 minutes, and the change in the 5% scenario is calculated as (42 - 38) = 4 minutes. The thawing process with a base time of 40 minutes shows the highest sensitivity as a ±20% change translates into a large absolute time variation 16 minutes. Note that the The ±5%, ±10%, and ±20% in the sensitivity analysis apply to each process independently, rather than in conjunction. For every scenario, the changeover time of one process is adjusted while all other parameters remain fixed, allowing marginal effect of that single process to be isolated.

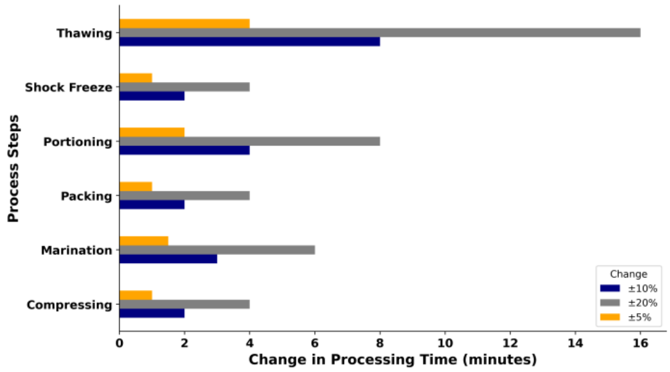

Fig. 5. Sensitivity analysis on changeover time for three scenarios ± 5%, ± 10%, and ± 20%

Figure 6 shows the sensitivity of total lead time to the change in changeover time, indicating a definite opportunity for lean improvements like applying SMED (Single-Minute Exchange of Die) can result in substantial time savings across the production process. Stakeholders can benefits from this analysis to prioritize operational bottlenecks and establish enhancement approach for continuous improvements and reduce non-value added time at transitions between processes.

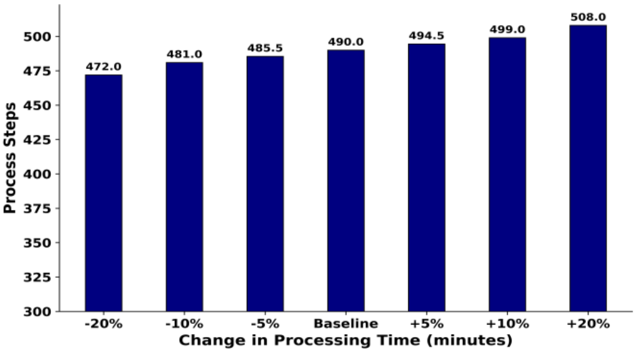

Fig. 6. The total Lead Time under changeover time scenarios

4. Discussion

The results of this study verify that a more thorough and precise understanding of inefficiencies in food processing operations may be obtained by applying Lean methods in conjunction with probabilistic simulation. This probabilistic framework exceeds simple Lean assessments and captures the intrinsic unpredictability of perishable food production. Particularly, the Thawing and Packing stages emerged as the dominant bottlenecks, contributing disproportionately to lead time variability. These results reinforce the argument that in food systems, delays are often concentrated in a few critical transitions rather than evenly distributed across processes. Furthermore, the sensitivity analysis reveals the vulnerability of upstream transitions in frozen food production, indicating that little inefficiencies at pivotal points can escalate into significant systemic delays.

The results of this study verify that a more detailed understanding of inefficiencies in food processing operations may be obtained by integrating Lean methods with probabilistic simulation. This probabilistic framework exceeds simple Lean assessments and captures the intrinsic unpredictability of perishable food production. Consistent with the broader literature, several patterns emerge regarding bottlenecks and improvements mechanisms in food processing and adjacent production environments (Garcia-Garcia et al., 2022; Psomas and Deliou, 2024). Across studies, tools such as VSM, SMED, 5S, and structured training consistently demonstrate positive impacts on operational performance through the magnitude of gains varies depending on where bottlenecks occur (Mathiyazhagan et al., 2022; Kleszcz, 2017).

Relative to this evidence base, our findings both align with and extend previous work. The reduction in changeover time reported by (Maalouf and Zaduminska 2019) reflect similar leverage points identified in the presented case, where changeover particularly in Thawing and Packing proved decisive for system performance. Likewise, (Veseli et al., 2024) emphasize the efficiency and sustainability gains associated with Lean practices. The presented research complements these contributions by illustrating how variability at critical stages, rather than mean times alone, drives disproportionate delays in food processing systems. By demonstrating the systemic impact of variability driven bottlenecks, this study expand the existing literature and offers managers a more targeted prioritization framework than conventional Lean assessments alone. These results reinforce the argument that in food systems, delays are often concentrated in a few critical transitions rather than evenly distributed across processes. Furthermore, the sensitivity analysis reveals the vulnerability of upstream transitions in frozen food production, indicating that little inefficiencies at pivotal points can escalate into significant systemic delays.

From a managerial standpoint, these findings present two distinct courses of action. First, the disproportionate impact of changeover times makes techniques such as SMED (Single-Minute Exchange of Die) highly relevant for food processing, despite their traditional association with discrete manufacturing. Reducing changeover complexity at the Thawing and Packing stages can yield substantial improvements in both efficiency and predictability. Second, the integration of sensitivity analysis with Lean and simulation equips managers with a prioritization framework: improvements should be directed not only at visible bottlenecks but also at processes most sensitive to variability. By focusing on these leverage points, managers can achieve faster cycle times, reduce non-value-added activity, and enhance resilience against demand fluctuations.

5. Conclusion

This study addresses the identified gap by proposing a practical and structured framework that integrates Lean manufacturing tools with simulation-based analysis. To account for real-world variability and operational uncertainty a Monte Carlo simulation is incorporated, providing a more robust and data-driven foundation for decision-making. Moreover, the integration of Monte Carlo Simulation with Lean promotes a systems-thinking perspective, by showing how enhancements can result in wider system-wide advantages. This promotes interdisciplinary collaboration and improves decision-making in complex, dynamic environments, which are significant difficulties frequently faced in food production systems.

Beyond advancing methodological integration, the study contributes to the broader Lean literature by tailoring established techniques to the unique characteristics of the food sector, where variability and resource sensitivity present persistent challenges. The results showed that the average processing time was approximately 355 minutes, with Thawing and Packing identified as the most significant contributors to total lead time. The sensitivity evaluation provided an additional layer of insight into process stability. By adjusting changeover times for each stage by ±5%, ±10%, and ±20%, the results showed that Thawing, with a base time of 40 minutes, was particularly vulnerable. A ±20% adjustment in this stage translated into a 16-minute swing in total lead time, the largest variation among all processes. These findings emphasize the importance of addressing high-impact processes when aiming to reduce variability and optimize performance. The findings support the hypothesis by illustrating that the amalgamation of Lean principles with probabilistic simulation produces a more comprehensive and sophisticated evaluation of waste-reduction prospects. While deterministic Lean tools identified Thawing and Packing as bottlenecks, the Monte Carlo and sensitivity analyses quantified the magnitude of variability and its impact on total lead time.

The presented methodology enhances the practical application of Lean principles by employing a data-driven, uncertainty-aware approach, thereby contributing to Lean literature and aligning with sustainability and resource efficiency objectives. Despite its contributions, this work has its own limitations. The investigation was confined to a food processing context, and the results may not be immediately applicable to other manufacturing sectors. Future research could extend this methodology to a wider range of industries to validate its scalability and adaptability. Moreover, the Value Stream Map (VSM) used in the study presents a static representation of the process, which can dismiss dynamic parameters such as machine failures, labor variability, or changes in batch size. Future research could expand the scope to include dynamic VSM, cost modelling, and real-time data inputs to provide even deeper insights into system behaviour and further enhance operational decision-making.

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