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A HYBRID SIMULATION-BASED APPROACH FOR ADAPTIVE PRODUCTION AND DEMAND MANAGEMENT IN COMPETITIVE MARKETS

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ABSTRACT

Managing production, inventory, and demand forecasting in a competitive market is challenging due to consumer behavior and market dynamics. Inefficient forecasting can lead to inadequate inventory, an interrupted production schedule, and eventually, less profit. This study presents a simulation-based decision support framework integrating discrete event simulation (DES) and system dynamics (SD). DES models production and inventory management to ensure optimized resource utilization, while SD is employed to incorporate market dynamics. This model jointly determines demand through purchase decisions from potential users and replacement demand from existing adopters. Further refinements prevent sales declines and sustain long-term market stability. This hybrid simulation approach provides insights into demand evolution and inventory optimization, aiding strategic decision-making. Finally, we propose and integrate a dynamic marketing strategy algorithm with the simulation model, which results in around 38% more demand growth than the existing demand curve. The proposed approach was validated through rigorous experimentation and optimization analysis.

1 INTRODUCTION

In today's dynamic market environment, businesses must continuously adapt to fluctuations in demand, competitive pressures, and operational constraints to maintain efficiency and profitability. Traditional production planning methods often rely on static models that fail to account for real-time market influences, leading to inefficiencies in inventory management and demand forecasting. To address these challenges, this study leverages a hybrid simulation approach that integrates SD and DES to optimize market-driven production planning. The concept of hybrid simulation (HS) has been present since the early development of simulation as a formal discipline. Initially, HS was defined as the integration of discrete-variable models with continuous-variable models or as the combination of simulation with analytical techniques such as optimization by Shanthikumar and Sargent (1983). Eldabi et al. (2016) explains a clear and unified definition remains lacking where they seek to explore the evolution of HS over time, aiming to establish the foundations of a structured approach by tracing the historical development of hybrid models. They also mention that the earliest hybrid simulation-analytic models likely combined discrete and continuous approaches, utilizing both differential equations and discrete events to represent systems that encompass both continuous dynamics and discrete occurrences. Mustafee and Powell (2018) classified hybrid simulation (HS) models into three types, where Type 1 models integrate both discrete and continuous components, such as those combining DES and SD. The second Type models consist solely of either discrete or continuous elements, without mixing both, exemplified by the combination of agent-based simulation (ABS) and DES.

The Third one represents a comprehensive hybrid approach, incorporating elements from both Type 1 and Type 2, such as those integrating ABS, SD, and DES within a single framework. Early implementations of HS were primarily driven by practical considerations, often stemming from computational programming needs or analytical problem-solving approaches. These early efforts focused on leveraging the strengths of different modeling techniques to enhance simulation accuracy, computational efficiency, and problem-solving capabilities in complex systems. Over time, the scope of HS has expanded beyond its initial pragmatic applications, evolving into a sophisticated approach used across various domains, including business, healthcare, and engineering, to address multifaceted decision-making challenges. DES is widely used in manufacturing systems to model production processes, inventory management, and supply chain dynamics. It captures discrete events such as order arrivals, production cycles, and inventory restocking, making it suitable for simulating operational workflows with high granularity. However, DES alone does not account for the behavioral and market-driven factors influencing demand. On the other hand, SD provides a macro-level approach to understanding complex interdependencies between market variables, such as customer adoption, promotional influences, and competitive market dynamics. By combining these two simulation paradigms, this study presents a comprehensive framework for modeling production and inventory while dynamically responding to demand fluctuations.

1.1 Related Work

The demand forecasting model in this study is based on the Bass Diffusion Model, which captures how new products are adopted over time through external influences advertising and internal influences the word-of-mouth (Jafari et al. 2014). Potential users make purchase decisions based on promotional activities, while existing customers contribute to replacement demand. Initially, the considered product had low demand; however, after analyzing a competing product's market performance, modifications were made to the influencing factors—such as advertising effectiveness, contact rate, and credibility—resulting in increased demand and sales. Additionally, further enhancements were implemented to sustain demand over time, ensuring stable market penetration. By dynamically adjusting marketing parameters and integrating production output with demand evolution, this study provides a robust decision-support tool for manufacturers. The simulation framework, developed in AnyLogic, enables businesses to evaluate various scenarios, test different promotional strategies, and optimize production planning based on market conditions. This research contributes to the field of hybrid simulation modeling by demonstrating how DES and SD can be effectively combined to bridge the gap between operational efficiency and market responsiveness. Furthermore, Torres et al. (2017) illustrated that SD can be integrated with scenario theory, which accounts for the ever-evolving external business environment, to provide a more comprehensive analytical framework. This combination enables managers to not only formulate more effective strategies but also gain deeper insights into the potential outcomes of various decision-making approaches. By incorporating scenario analysis, the industry can better anticipate market shifts, assess the long-term impact of their strategic choices, and enhance their adaptability in a competitive landscape.

Their approach empowers managers with data-driven insights, allowing them to make well-informed decisions that align with both internal objectives and external market dynamics, but they didn't consider the main manufacturing strategy in their research. Jahangirian et al. (2010) presents a result of a literature review between 1997 to 2006 where they show the logic behind using DES for different types of manufacturing that can give information on lead time, resource allocation, and Production scheduling. Hence, it is clear from their experiment that DES is the most efficient and effective tools for modelling manufacturing and operational activities. This is one of the motivations for integrating DES into our research for getting a clear picture of real scenarios that capture market demand based on the floor activities. Though Mustafee and Powell (2018) illustrate HS as mostly been used in isolation, But Brailsford et al. (2018) highlighted that the integration of SD and DES is the most frequently utilized approach in hybrid modeling, where we can consider real world, mixed and illustrative data that enables managers to comprehend the overall system better. Although HS is a widely used modeling technique in business, a review of the literature reveals that its application in strategic management has not been extensively explored (Mustafee et al. 2017; Brailsford et al. 2019). Therefore, this paper aims to introduce a modeling development process that can support strategic decision-making in business using both DES and SD. The study seeks to examine the applicability and advantages of the two-paradigm HS approach in strategy development and analysis. We develop a hypothetical HS model based on production data that gives information on inventory and experimental analysis through scenarios. Another study by Howick and Ackermann (2011) on the practical application of mixed operations methods features several reasons for their integration. These include managing complex problem systems, supporting different project phases, leveraging the unique advantages of specific methods, and addressing the limitations of individual approaches, but the plant's production system is not integrated at all in their modeling. Though Korder et al. (2024) highlight the importance of hybrid simulation in analyzing supply chain disruptions, they primarily focus on operational challenges rather than broader strategic implications. However, Camur et al. (2023) demonstrated that integrating Discrete Event Simulation (DES) and System Dynamics (SD) paradigms in supply chain design enhances resilience and enables simultaneous consideration of system-wide interactions and detailed process flows, thus providing a more comprehensive understanding for decision-makers. Despite the increasing use of hybrid models in manufacturing and supply chain contexts, a review of the literature reveals that their application in strategic business planning, particularly in integrating market dynamics with production management, remains underexplored (Kunc 2019). Therefore, this paper aims to introduce a modeling development process that can support strategic decision-making in business using both DES and SD. The study seeks to investigate the applicability and benefits of this two-paradigm hybrid simulation approach in strategy development and evaluation. We build a hypothetical hybrid model that integrates production workflow and demand fluctuations, incorporating insights from real-world scheduling systems and illustrating potential performance outcomes through scenario-based experiments.

Table 1: Comparison of Hybrid Simulation Approaches in Production and Market Dynamics.

Paper Details	Method	Identified Gap
Jafari et al. (2014)	Bass Diffusion Model	No manufacturing system integration
Torres et al. (2017)	SD	No integration with production systems
Jahangirian et al. (2010)	DES	Highlights DES's strengths but no integration
Mustafee & Powell (2018)	HS	Limited strategic management applications
Brailsford et al. (2018)	HS (DES + SD)	No plant-level production integration
Howick & Ackermann (2011)	Mixed methods	No production system integration
Korder et al. (2024)	HS for SC disruptions	Lacks strategic business decision focus
Camur et al. (2023)	HS (DES + SD)	No integration with production-level strategy
Kunc (2019)	Review of HS models	Lacks strategic business application
Hoad & Kunc (2015)	HS (DES + SD)	Does not incorporate manufacturing activities
Our Proposed Method	HS (DES + SD)	Integrates plant production, market behavior, and profitability, while enabling experimentation and scenario analysis for strategic decision-making.

Hoad and Kunc (2015) examined how new practitioners adopt and apply both modeling approaches. The findings suggest they can learn both techniques, but DES controls the tangible system characteristics more easily than abstract concepts like feedback processes in SD. They didn't mention any manufacturing information integration into their approach. From the above several related discussions, we identify the gap in most of the articles in previous HS modelling that they do not use DES for analyzing plants manufacturing activities.

To address this critical gap (Table 1) and the challenge of managing fluctuating market demand for edible oil products and production at the same time, we integrate production and inventory data from a well-established edible oil industry with sales, ensuring a comprehensive approach to optimization. The demand for edible oil products is highly sensitive to factors like product shelf life, consumer preferences, and market conditions. Due to this, businesses must be agile in adjusting sales strategies, promotional activities, and advertising efforts to avoid overstocking or stockouts. We also identify the important factors affecting demand and implement the extended maturity stage for new product development. While short-term promotional strategies can temporarily boost demand, the long-term sustainability of these efforts is questionable without a more robust, adaptive demand management approach. The key challenge is to develop a strategy that not only boosts initial adoption rates but also ensures a steady demand throughout the product lifecycle. Rather than relying on increasing advertising spending or promotional offers, businesses need to identify the most effective combination of influencing factors to encourage long-term adoption and repeat purchases. To address these issues, the study proposes a simulation-based approach to help businesses model various strategies and assess their potential impact on demand before making real-world changes. By integrating DES for production output and SD for demand forecasting, the research aims to create a hybrid simulation model. This model dynamically adjusts key influencing parameters such as marketing interventions, consumer behavior, and external factors to maintain sustainable demand growth over time. Utilizing our proposed approach, businesses can experiment with different strategies in a controlled environment and make informed, data-driven decisions on how best to optimize their marketing efforts, ultimately leading to improved sales performance and more efficient resource utilization. The final deliverable includes a comprehensive analysis with visualizations of demand trends, production capacity, and the impact of various marketing strategies on overall sales. The findings can help decision-makers in manufacturing, retail, and consumer goods enhance their demand forecasting, inventory control, and overall supply chain performance in competitive environments. The specific contribution of this study is given below:

1. Developed a comprehensive framework to transform a low-demand edible oil into a high-demand product by optimizing marketing parameters, such as advertising strategies, pricing models, and consumer engagement.
2. Illustrate a hybrid simulation method that captures the product's life cycle behavior and supports sustained demand at the maturity stage through a dynamic marketing strategy.
3. Perform multi-scenario experimentation to evaluate the impact of various influencing factors on the market growth and profit gain.

While this paper primarily focuses on optimizing demand and production strategies for new edible oil products with initially low demand, the framework's flexibility allows it to be extended to mature products with some adjustments. For mature products, marketing and promotional strategies might focus less on initial adoption and more on sustaining brand loyalty, managing replacement demand, and optimizing inventory levels. The hybrid simulation approach can incorporate these strategies by modifying the parameters of the System Dynamics model, such as reducing the weight of innovation (p) and increasing the importance of replacement demand from existing customers. However, traditional demand forecasting methods might indeed be more appropriate for highly stable, mature products with predictable sales patterns. Therefore, the primary intention of this framework is to support new product decisions and dynamic markets. This distinction strengthens the relevance of the proposed approach, highlighting its value in guiding strategic decision-making where market dynamics are less predictable. The remainder of this study is structured as follows: Section 2 presents the problem statement that serves as the foundation for this research. Section 3 outlines the proposed methodology. Section 4 details the experimental setup and discuss about the results. Finally, Sections 5 and 6 conclude the paper by summarizing the research findings , limitations, and discussing the practical implications.

2 PROBLEM STATEMENT

This paper presents a challenging demand and production strategy for edible oil companies in Bangladesh. The market demand for edible oil products fluctuates frequently due to their limited shelf life and changing consumer preferences. To maintain sales within the product's lifetime, businesses must continually adjust sales strategies, promotional activities, and advertising efforts. Unlike durable goods, edible oil products require a highly responsive marketing approach to ensure steady sales and prevent excess inventory or stockouts. In this case, the aforementioned company enters a competitive market with a new edible oil brand, which struggles with low initial demand, leading to stagnation in sales and inefficient utilization of production capacity. Traditional demand forecasting models have proven ineffective in capturing the dynamic nature of consumer adoption and external market influences. Upon analyzing competitor products from other existing companies, we identified the critical factors that influence advertising effectiveness, contact rate, contact effect, and credibility. These factors play a crucial role in stimulating demand. However, the company lacks a well-optimized strategy to leverage these factors and their dynamics, which results in poor market penetration and customer adoption. While short-term marketing interventions can generate a temporary increase in demand, there remains a risk of a declining sales trend over time unless a sustainable strategy is implemented. As such, the challenges are not only to increase the initial adoption rate but also to maintain demand at an optimal level throughout the product's lifecycle. This study presents a hybrid simulation model that combines Discrete Event Simulation (DES) for production output and System Dynamics (SD) for demand forecasting. The model dynamically adjusts key parameters to support sustained demand growth. This approach allows businesses to test multiple demand and inventory management strategies in a digital environment before applying them in real operations. The findings of this study provide actionable insights for decision-makers to enhance demand forecasting, optimize inventory levels, and sustain a competitive advantage in the edible oil industry.

3 METHODOLOGY

As shown in Figure 1, the proposed methodology is described in three different modules: 1) DES model for production operations, 2) SD model for demand analysis by capturing the market dynamics, and 3) Experimentation with different system boundaries and parameters. A step-by-step explanation of this framework is provided in the following subsections.

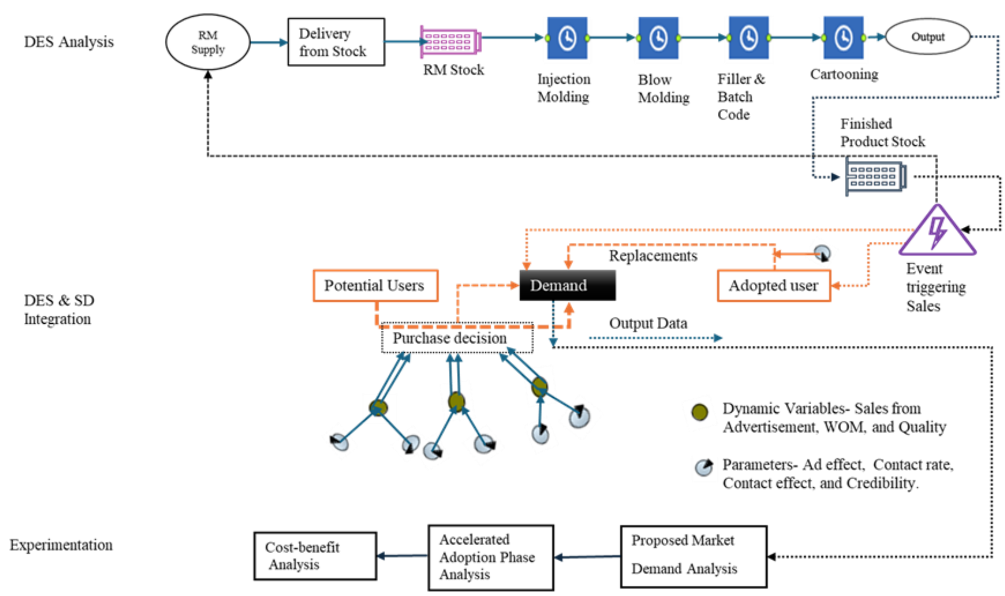


Figure 1: Methodology framework for hybrid simulation.

3.1 DES Model for Production Operations

This section represents the key operational activities within the edible oil manufacturing supply chain, capturing material flow, processing stages, and inventory dynamics. In this research, we built the simulation model using AnyLogic (Rahman et al. 2023; Borshchev 2014), a versatile hybrid and multi-paradigm simulation software that enables the integration of various modeling approaches within a unified platform. The model begins with raw material supply, followed by delivery to stock, where replenishment logic ensures material availability. The production process (Kamal and Rahman, 2024) includes injection molding, blow molding, filling, batch coding, and cartooning, leading to finished product storage. The processing time for each of these workstations was considered according to the triangular distribution ~ $T(a, b, c)$. Here, a, b, and c indicate the minimum, mode, and maximum processing time, respectively. For example, the delay time or (processing time) for cartooning is $T(2, 2.5, 3)$ minutes. The dataset used in this simulation study was obtained through a collaboration with a well-established edible oil manufacturing company in Bangladesh. Key operational data, including raw material inflow rates, processing times, production cycles, and historical demand trends were extracted from the company's internal Enterprise Resource Planning (ERP) and Manufacturing Execution Systems (MES). To ensure the accuracy and reliability of the data, a multi-step verification process was conducted. First, the data was cross-validated with historical production records and monthly inventory reports to confirm consistency. Additionally, direct interviews with production managers and supply chain experts were held to validate key parameters such as processing times, inventory levels, advertising effectiveness, credibility, contact rate, etc. This adaptive inventory control mechanism (Figure 1) dynamically adjusts order quantities based on demand fluctuations, preventing shortages while optimizing holding costs. Real-time monitoring and event-driven decision-making enhance system efficiency, ensuring seamless operations across the production network. In traditional inventory management systems, replenishment is often based on fixed reorder points or periodic review methods (Mehrotra and Sehgal, 2024), which can lead to inefficiencies such as stockouts or excessive holding costs.

To address these limitations, this study employs a DES framework (Figure 1) to implement a dynamic inventory replenishment strategy within the supply chain. At the Raw Material Supply (RMSupply) stage, a logic-based mechanism determines order quantity based on finished goods stock levels. If finished goods stock (FGStock) falls below the required units (for example, we consider 30 in this model), the system triggers a large order of user-required units to prevent disruptions. Otherwise, a smaller order of m units is placed to maintain stock balance and avoid overstocking. This approach benefits over traditional fixed-order models by adapting order quantities dynamically based on real-time conditions. To further optimize supply chain efficiency, a holistic inventory calculation aggregates stock across multiple stages, including supplier stock, delivery stock, finished goods stock, work-in-progress inventory, and raw material stock. When the on-hand inventory level drops below a predefined reorder point, a raw material supply order is automatically placed to maintain operational continuity. This real-time monitoring mechanism ensures responsiveness to demand fluctuations, overcoming the limitations of traditional models that rely on historical data. Additionally, the simulation integrates an inventory vs. manufacturing strategy tracker, which continuously monitors stock levels and adjusts ordering policies dynamically. By leveraging DES-based real-time inventory tracking, dynamic order quantity adjustments, and continuous monitoring, this methodology provides a more agile, cost-effective, and resilient inventory management approach for the edible oil industry.

3.2 Integration of SD to Capture the Market Dynamics

The aim of this section is to integrate the DES model with SD to analyze the hybrid simulation system for market analysis. To do so, we deploy the AnyLogic Event (Event Triggering sales) block, where the java function performs the desired condition to get stock information from DES. Then using this stock information (obtained from Step-1), we incorporate dynamic variables and parameters that influence the demand and marketing strategy of a new product development. For analyzing the behavior of these variables, we apply the Bass diffusion model (Santa-Eulalia et al. 2011) into this SD simulation using the Equation (1) for getting the information on the coefficient of innovation & imitation in our model:

$$\frac{dN(t)}{dt} = p \cdot \left(M - N(t)\right) + q \cdot \frac{N(t)}{M} \cdot \left(M - N(t)\right) \tag{1}$$

Where $N(t)$ is cumulative number of adopters at time t, M is the total potential market size (number of potential adopters), p is the coefficient of innovation (probability of adoption due to external influence like advertising), q is coefficient of imitation, in other words, the probability of adoption due to the word of mouth (WOM) effect. In this section, SD captures the aggregate demand dynamics by modeling the transition of potential users to adopted users, driven by innovation (external influence) and imitation (WOM effects). In a market, WOM serves as a powerful form of informal communication, providing a competitive advantage. The integration occurs through event triggers, where changes in demand from the SD model initiate purchase events in DES, and real-time feedback from DES updates the SD parameters, ensuring dynamic system behavior. Based on the dynamic variable (Advertising effect, WOM), this model calculates purchase decisions that are added to the market demand. The adopted user (who already purchased the products) gives replacement decisions based on product lifetime, which is also a significant factor that updates the demand. This hybrid approach enables businesses, particularly in the edible oil industry, to better anticipate market fluctuations, optimize production and inventory levels, and improve decision-making by combining the predictive power of SD with the granular insights of DES.

Table 2: Market Dynamics Simulation Algorithm.

***Input**: Cnrate, cnefect, AdEffect, credibility (Parameters)*
***Output**: Customer Demand Quantity Based on the value of Promotional Strategy.*
***Initialization**: CDemand Rate, PotentialUsers for the Day D_l where l=1,2,3…. Product Lifetime (days); The promotional effects change rate Cijk where ijk represents the variation in effect measurements based on observed managerial insights. conditionExecuted as true and conditionStartDay = 1;*

```
for (int day=D_l; day <D_PLT; D++) {// PLT is Product Lifetime.
If (CDemand<=n & PotentialUsers <=m) {// n,m minimum rate considered by authority
for (month=1; month <12; month ++) {//Since Product lifetime 1 year
Update the value of Cnrate, cnefect, AdEffect, credibility
Updating the values =(random.nextDouble() * 2-1) *Cijk * Parameters;// Updating the
values based on condition.
        }// Closing first condition
      } // Closing second condition
    };// Closing third condition
If (! conditionExecuted) {// When demand falls below certain amount
Initialization: conditionStartDay = day;
        }; End of the loop
 if (conditionExecuted && day - conditionStartDay <=D) {
PotentialUsers = x;//x is the value to update as required
else if (conditionExecuted && day - conditionStartDay >= D) {
PotentialUsers -= P; /P-the value user can update as required.
PotentialUsers = Math.max (100, PotentialUsers);// minimum threshold.
    }
  };
End
```

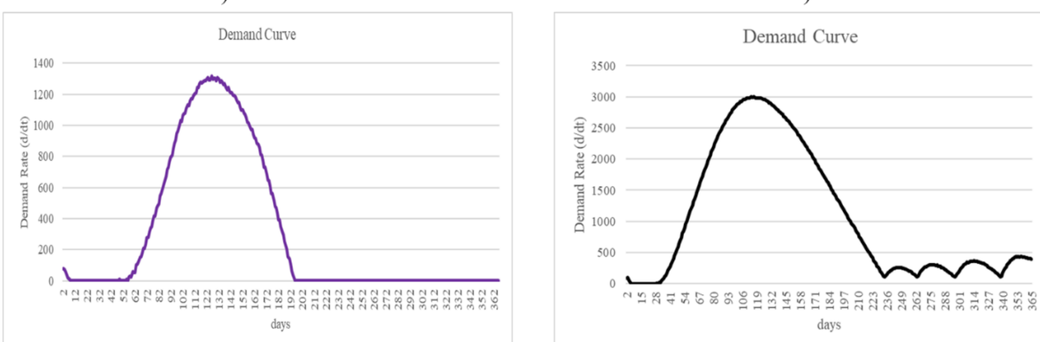
3.3 Experimentation on the Output Data

Once we observed the data on marketing strategy parameters, obtained from the SD model as described above, we integrate them using the algorithm as outlined in (Table 2). In this algorithm, we consider the key parameters from the bass diffusion model that affect the demand. This algorithm models market dynamics by adjusting key parameters over time based on customer demand (*Demand*) and market potential (*PotentialUsers*). It iterates daily from the first day to product lifetime, checking if Customer Demand and Potential user numbers fall from certain user defined requirements. Then it triggers a series of random adjustments to credibility, conversion rate (*Cnrate*), advertising effectiveness (*AdEffect*), and

PotentialUsers. These parameters fluctuate within predefined ranges using random values to simulate real-world uncertainties. The algorithm ensures that if the condition is met for the first time, *conditionExecuted* is set to true, and the current day is recorded as *conditionStartDay*. In the beginning, *PotentialUsers* stabilized at a rate the user required to reflect short-term market recovery due to promotional efforts and credibility gains. For example, we consider at least 1000 potential users after the first few days. However, once these days have passed, *PotentialUsers* begin to decline until they reach close to zero. This gradual decline represents the long-term decay in the market impact, where initial boosts in market penetration fade over time. By incorporating stochastic variations in key parameters, the model captures the cyclical nature of demand. This provides a realistic simulation of customer acquisition, retention, and market shrinkage due to reduced credibility and advertising effectiveness. Once the desired demand curve with extended maturity stage achieved (Figure 2) using the proposed algorithm, we calculate the overall profit and sales using Equation (2).

$$\text{Profit} = \sum_{i=1}^{n}(\text{TS}_i \times \text{SP}_i) - \sum_{i=1}^{n}(\text{IC}_i + \text{PC}_i + \text{MC}_i) \tag{2}$$

a) b)



Existing Demand

Proposed Demand with extended Growth stage

Figure 2: Demand Curve analysis.

where profit (P) is calculated as the total revenue, TS is total sale and SP is sales price, inventory cost is IC, PC is production variable cost, and MC is marketing cost. Here, n represents the total number of periods (product lifetimes). After getting a profit scheme from the base model, we implemented the results to the AnyLogic Experimentation section to examine the effects of parameters on overall profit. For this purpose, we consider several replications for each of the main influencing parameters that affect consumer demand. A detailed analysis of the experimental set-up will be discussed in the following sections.

4 RESULTS & ANALYSIS

This section presents the evaluation of key performance metrics, including holding cost, ordering cost, contact effect, contact rate, quality issues, and profit over multiple stages. The analysis includes 1) the effects of the parameters' variation and their impact on profitability, and 2) an optimization experiment to select the best possible combination of parameters that ensures the most profitability. At the first step, we observe that the higher ordering costs lead to increased expenses per transaction, directly affecting net profitability, whereas the variations in contact rate determine the efficiency of stock turnover and its impact on holding costs. We ran the optimization experiment six times (replications) and recorded the output in Table 3. Clearly, the variations in contact rate and ordering cost exhibit distinct influences on profit levels. A higher ordering cost increases the total expenses incurred per replenishment, which can reduce profit if not offset by an efficient ordering strategy. Similarly, fluctuations in contact rate alter inventory availability and stock movement efficiency. For instance, in run 2 and run 6, where the contact rate is higher (0.4 and

0.2, respectively), the profits were relatively lower, indicating that frequent order placements and increased holding costs negatively impacted revenue.

Table 3: Evaluation Metrics for Experimental Analysis.

Runs	1	2	3	4	5	6	Optimization
Ad-effect (%)	0.007	0.0056	0.0048	0.0048	0.005	0.005	0.006
Contact Rate (%)	0.35	0.31	0.4	0.4	0.3	0.2	0.324
Holding Cost ($)	1.1	1.4	1.01	1.3	1.2	1.5	1.174
Ordering cost, ($)	0.372	0.5	0.412	0.6	0.417	0.439	0.574
Contact Effect (%)	0.23	0.22	0.31	0.31	0.24	0.2	0.21
Credibility (%)	0.0005	0.0005	0.00049	0.00047	0.00049	0.00047	0.0004
Profit ($)	51772	46862	57532	49542	50514	43990	53603

In contrast, run 3 (contact rate 0.4 %, holding cost $ 1.01, Ordering Cost $ 0.412) achieved the highest profit is $57,532, suggesting that moderate ordering costs and optimized inventory turnover led to improved profitability. The profit trend scenarios from the comparison of four simulation replications (Run 1 to Run 4) highlight the impact of ordering cost variations. Experimental runs with lower ordering costs (around 0.35-0.37) consistently perform better in terms of profitability in this case. In contrast, higher ordering costs (above $0.4) led to fluctuations and a gradual decline in overall profit accumulation. The profit curve for the first two runs demonstrates relatively stable and increasing profit trends, indicating that a lower ordering cost strategy coupled with a balanced contact rate ensures steady revenue growth.

a) b)

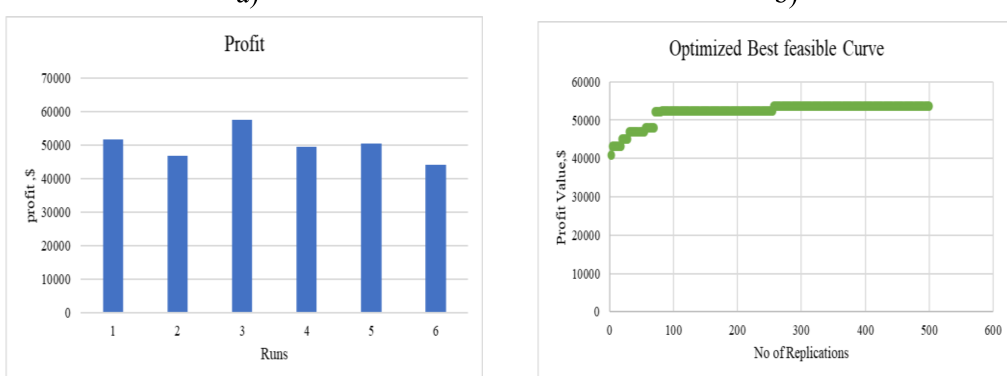


Figure 3: Experimental analysis- a) Profit from compare runs and, b) Parameter optimization from optimization experiments.

However, in the 2nd and 3rd runs, we observe lower profit growth, which relates to increased inventory costs, leading to inefficiencies in maintaining stock at optimal levels. The highest profit observed during these runs around $57,532, whereas the lowest profit fell to approximately $43,990 (Figure 3-a). These fluctuations indicated a lack of stability in the setup, necessitating a more robust optimization approach. Hence, we conducted the optimization experiment to determine the best possible parameter combination for maximizing profit in an inventory system.

While the previous stage involved six replications, this phase focused on iterative optimization to refine and improve decision-making by systematically exploring feasible parameter sets. The experiment completed 501 iterations with the best feasible solution achieved at iteration 257, yielding a maximum profit of $53,603.69, an improvement over the initial objective of $48,866.08. These values are optimized to ensure that the supply chain maintains a balance between stock availability and cost efficiency while minimizing excessive expenses. We maintained the lead time of 346 days as product lifetime, ensuring that the production and replenishment cycles remained within an acceptable range. In the previous six replications, the inventory system exhibited fluctuations in profit due to variations in Contact Rate, advertising effect, Holding Cost, and Ordering Cost (Table 3). The current optimization process systematically tested multiple configurations to find the most efficient balance between ordering frequency, inventory holding, and replenishment strategy. The profit diagram (Figure 3-b) illustrates the best feasible solutions obtained across multiple iterations. The optimization process steadily improved results, with profits increasing sharply in the first 100 iterations, before stabilizing at approximately $53,000-$54,000 in later stages. This suggests that the algorithm efficiently converged to an optimal solution, ensuring that further adjustments yielded minimal improvements. The best feasible solution demonstrates how systematic parameter tuning resulted in a stable and optimized inventory strategy, ultimately maximizing profitability.

5 CONCLUSION

This paper presents a simulation-based approach for optimizing production operations by considering demand and market dynamics, specifically tailored for the edible oil industry. Leveraging this hybrid method, companies can explore and evaluate various marketing strategies, assess the effects of influencing factors, and anticipate demand fluctuations without making immediate adjustments to their actual systems. Unlike traditional forecasting methods that struggle to capture dynamic consumer behavior and shifting market conditions, this hybrid simulation approach offers a reliable and insightful platform for strategic decision-making. In an increasingly competitive marketplace, this method allows companies to respond swiftly to changes, reduce operational risks, and maintain consistent market presence while minimizing costs and inefficiencies. Although our optimization experiments successfully identified the optimal inventory management strategy, several avenues remain open for future exploration. Incorporating seasonal variations in demand and dynamic lead-time fluctuations could significantly enhance the model's adaptability to real-world uncertainties. Furthermore, external validation across diverse market scenarios and varied cost structures would improve the robustness and generalizability of the findings. However, this study provides several recommendations with clear practical implications for industry practitioners.

6 PRACTICAL IMPLICATIONS

By deploying the hybrid simulation framework integrating DES and SD, managers can proactively evaluate strategic adjustments in production and marketing, effectively aligning operations with consumer demand patterns. The real-time analysis capability of the model enables swift responses to sudden shifts in market trends, minimizing stockouts and surplus inventory. This predictive approach supports efficient resource allocation and helps businesses avoid unnecessary costs associated with excess production or inventory shortages. Additionally, the method allows firms to experiment with marketing scenarios virtually, significantly reducing the financial and operational risks linked to untested promotional campaigns. Ultimately, this enhances the agility of enterprises, ensuring sustained profitability and competitive advantage by optimizing both inventory management practices and market penetration strategies in uncertain and dynamic consumer environments.

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