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Optimizing Gondola Replenishment: A Simulation Approach Using Promodel and Evolutionary Algorithms to Balance Costs

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Abstract. Processes within the supermarket retail sector necessitate continuous enhancements to minimize expenditures and maintain competitiveness. This research endeavors to develop a model and simulate the gondola replenishment process at a point of sale located in Guayaquil, Ecuador. The modeling incorporates relevant factors such as merchandise restocking to estimate the personnel required for adequate product replenishment. The simulation methodology allows for modeling a point of sale through various merchandise supply scenarios and estimating the optimal number of personnel needed. The simulation and its components are established based on observed processes, with merchandise boxes identified as the primary unit of measure within the model, and data asymmetry evaluated using probability distributions. This modeling is executed using queuing theory and evolutionary algorithms via Promodel software, with the SimRunner optimizer used to identify the optimal staffing levels. Given the complexities associated with mathematical programming and specialized software such as the General Algebraic Modeling System, this research presents an accessible and readily applicable alternative solution for planning managers.
Keywords: Gondola Replenishment, Supermarket Simulation, Workforce Optimization, Promodel, SimRunner,Retail Operations

1 Introduction

In recent years, the literature on modeling and simulation in retail logistics processes has advanced significantly. Recent studies, such as Zhang et al. (2023) and López & Ramírez (2024), have demonstrated that discrete-event simulation enables the optimization of human

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resource allocation in self-service stores, achieving up to a 15% reduction in operating costs and improvements in customer service indicators. Furthermore, contemporary research highlights the integration of real-time demand forecasting and artificial intelligence techniques to dynamically adjust the number of operators, increasing efficiency and adaptability to seasonal variations. These contributions support the relevance and timeliness of the approach adopted in this study, justifying the methodological update employed. This context sets the stage for examining practical applications where such methodological refinements can have a tangible impact, particularly in complex and dynamic environments like retail supply chains.

In the fiercely competitive supermarket retail sector, maintaining optimal product availability and ensuring excellent customer service are paramount. These factors significantly influence a supermarket's ability to attract and retain customers, directly impacting its profitability and market position [1]. Efficient and effective replenishment of gondolas, the shelving units that display products to customers, is a critical operational process that directly affects both product availability and service quality. Moreover, recent studies highlight the growing importance of integrating sustainability considerations into retail operations, emphasizing efficient resource utilization and waste reduction [2]. This research addresses the challenge of optimizing gondola replenishment within a supermarket in Guayaquil, Ecuador. The central problem is determining the optimal number of personnel required to efficiently stock the gondolas while simultaneously minimizing labor costs and maximizing customer service levels. Traditional approaches often rely on subjective assessments made by store managers based on comparisons with other stores, lacking a technical and data-driven foundation. This can lead to either understaffing, resulting in empty shelves and dissatisfied customers, or overstaffing, leading to unnecessary labor expenses. Furthermore, the increasing complexity of retail operations, driven by factors such as personalized customer demands and omnichannel fulfillment strategies, necessitates more sophisticated approaches to resource allocation [3]. The study aims to provide a planning solution, grounded in simulation and optimization techniques, for determining the ideal staffing levels for gondola replenishment. This solution aims to provide operational excellence, improve customer service quality, improve employee satisfaction by reducing workloads, and improve employee retention rates. By leveraging advanced simulation methodologies and incorporating real-time data analytics, this research seeks to contribute to the development of more agile and resilient retail supply chains [21]. In Ecuador, the retail segment exhibits constant evolution [5]. Local economic reports focused on the income and profit margins of the most profitable companies detail in their annual publications that the top-earning companies in 2019 included three supermarket chains. These figures highlight the substantial revenues generated by these companies within the Ecuadorian market, as detailed in Table 1

Table 1. Revenue Ranking in 2019 of the 3 Largest Supermarket Chains in Ecuador

Ranking	Corporation	Revenue 2019 (Millions)
Rank 1	Corporación Favorita C.A	2104
Rank 4	Corporación El Rosado S.A	1188
Rank 11	TIA	709

Source: Self-elaboration, based on data presented in Revista Ekos 2019

The methodological framework developed here responds directly to contemporary challenges in industrial systems management, emphasizing engineering applications, efficiency improvement, and industrial innovation.

2 Materials and Methods

This research employed simulation modeling to analyze and optimize the gondola replenishment process in a supermarket located in Guayaquil, Ecuador. The simulation approach facilitates the evaluation of various stocking scenarios and the determination of the optimal number of personnel required while considering the complexities of real-world operations [6]. The subsequent sections detail the theoretical background, software utilized, and methodological steps undertaken.

2.1 Simulation Modeling Framework

Simulation, as defined [7], involves the creation of a model that mimics the behavior of a real-world system, enabling experimentation and analysis without disrupting the actual system. Discrete-event simulation (DES), in particular, is well-suited for modeling systems with stochastic elements and sequential processes, such as the supermarket replenishment process [8]. Advances in agent-based modeling have further enhanced simulation capabilities, allowing for the representation of individual decision-making and interactions within complex systems [9]. A simulation model comprises logical, mathematical, and probabilistic relationships that represent the behavior of the system under study when subjected to specific events [10], as depicted in Figure 1. As computer simulation involves iterative executions to understand the complex relationships within a system. Therefore, a simulation study should be planned as a series of experiments following established design of experiments principles to ensure meaningful interpretation of results [11]. Sensitivity analysis techniques, such as those described by [12], can further enhance the understanding of model behavior and identify critical parameters.

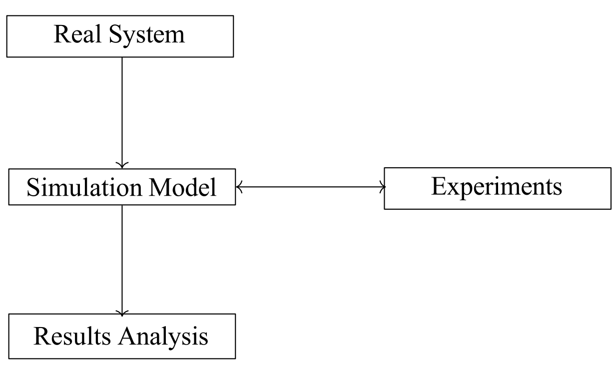

Figure 1. General Outline of a Simulation Process. Systems with Return Logistics: Application to the case of returnable containers.

2.2 Probability Distributions

Probability distributions are fundamental to stochastic simulation, enabling the representation of uncertainty and variability in system parameters [13]. Discrete random variables, characterized by specific parameters, are crucial for modeling events with distinct outcomes. The selection of appropriate distributions and validation of their fit to empirical data are critical steps in simulation modeling [14]. Recent research has focused on developing more robust methods for distribution fitting and parameter estimation in non-stationary systems [15].

This project involved identifying relevant probability distributions for key processes (see Table 5) and fitting them to empirical data collected from the supermarket.

Table 2. Processes and Distribution Functions

Process	Distribution Function	Parameters
Arrival	Normal	μ: mean σ: standard deviation
Reception	Poisson	μ: mean
Entering Warehouse	Uniform	μ: mean
Loading Gondola Cart	Uniform	μ: mean *h*: half range
Placing Product on Gondola	Normal	μ: mean σ: standard deviation

2.3 Simulation Software: Promodel

The simulation model was developed using Promodel simulation software [16], a commercial tool designed for building and analyzing discrete-event simulation models. Promodel offers a graphical user interface for model construction, animation capabilities for visualizing model behavior, and an integrated optimization tool called SimRunner for automated scenario analysis and optimization. Cloud-based simulation platforms and integration with real-time data streams represent emerging trends in simulation software [17]. According to Singer et al., Promodel can utilize (M/M/1) queuing models, where arrival and service times follow exponential distributions. Agent-based modeling is a technique to overcome that restriction. [18] describe the (M/M/1) queuing system as based on the following equations:

$$\bar{Q} = \frac{p^2}{1-p}, \quad \text{where } p = \frac{\lambda}{\mu} \text{ (server utilization)}$$

$$\bar{N} = \frac{p}{1-p} \quad \text{(avg. customers in system)}$$

$$\bar{W} = \frac{\bar{Q}}{\lambda} = \frac{p}{\mu(1-p)} \quad \text{(avg. time in queue)}$$

$$\bar{T} = \frac{\bar{N}}{\lambda} = \frac{1}{\mu-\lambda} \quad \text{(avg. time in system)}$$

$$P_0 = (1-p) \quad \text{(prob. system is empty)}$$

$$P_n = (1-p)p^n \quad \text{(prob. n customers in system)}$$

$$P(N > n) = p^n \quad \text{(prob. more than n customers)}$$

$$E(W \mid W > 0) = \frac{\bar{W}}{p} \quad \text{(expected waiting time, given wait)}$$

$$E(Q \mid Q > 0) = \frac{\bar{Q}}{p^2} \quad \text{(expected queue length, given queue)}$$

The primary components used in the Promodel simulation are summarized in Table 3

Table 3. Components Used for Simulation in Promodel

Component	Description
Locations	Represent physical areas in the system (e.g., warehouse, gondola)
Entities	Represent items flowing through the system (e.g., boxes of merchandise)
Resources	Represent movable elements (e.g., personnel)
Paths	Define routes for entities and resources
Variables	Store numerical information (e.g., arrival rates, processing times)
Distributions	Define stochastic behavior (e.g., inter-arrival times, service times)

2.4 Optimization with SimRunner

SimRunner, an integrated optimization tool within Promodel, enables the definition of optimization criteria and the use of evolutionary algorithms and direct search techniques to identify optimal solutions. Simulation optimization techniques have been widely applied in various domains, including supply chain management and healthcare [19]. Recent advances in metaheuristic optimization techniques have further enhanced the capabilities of SimRunner for identifying near-optimal solutions in complex scenarios [20]. notes that Promodel's SimRunner facilitates the optimization process by allowing the optimization of both integer and real decision variables using evolutionary algorithms. Surrogate-based optimization approaches have also emerged as effective methods for simulation optimization, particularly when dealing with computationally expensive simulation models [21]. Torczon's Multi-Directional Search highlights that direct search methods rely solely on function evaluation information, without requiring derivative information for determining descent directions. Bayesian optimization techniques have gained prominence for simulation optimization, offering a principled approach for balancing exploration and exploitation in the search for optimal solutions [22]. The interaction between these optimization algorithms and the Promodel simulation environment is illustrated in Figure 2, which demonstrates how decision variables from the optimizer are fed into the simulation model, and response variables from the simulation are used to guide the optimization process.

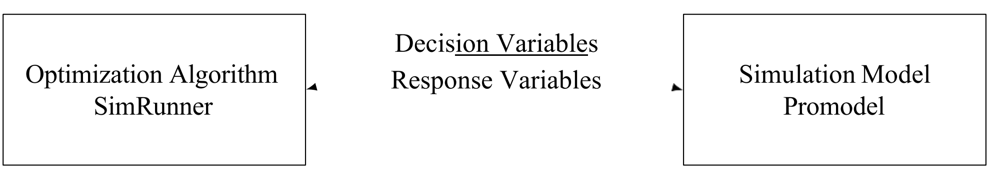

Figure 2. Interaction between Promodel and its Optimizer. Source: Adapted from [10]

2.5 Methodology

The study applies a quantitative engineering approach that combines process optimization and system modeling to test alternative operational scenarios and improve resource efficiency. This framework supports reproducibility and practical application in real industrial settings.

The methodology comprised data collection, model development, scenario execution, and optimization. The overall approach aligns with established simulation modeling guidelines [23].

2.5.1 Data Collection and Validation

Data collection involved gathering information on the supermarket's organizational structure, operating hours, processes for receiving and stocking merchandise, and policies regarding resource utilization and overtime. Data on merchandise box receipts, including date, time, number of boxes, and number of items received. Direct observation and interviews with supermarket staff were conducted to validate the accuracy of the collected data. This method is in accordance with Meredith, stating that observational studies can provide deep insight when used to study business processes. Process mining techniques can also be applied to analyze event logs and identify bottlenecks and inefficiencies in the replenishment process. Key findings from the data collection process included:

- The store encompasses 7832 m^2, with 5250 m^2 dedicated to display gondolas.
- The store operates from 9:00 AM to 10:00 PM, Monday through Sunday. Merchandise receiving occurs from 8:00 AM to 9:00 PM.
- The store receives multiple merchandise boxes daily from its distribution center and local suppliers.
- The Warehouse Manager physically receives the merchandise, inspecting each box for damage and verifying compliance with health and safety standards.
- Merchandise box arrivals at the warehouse follow a cyclical pattern, as detailed in Table 4
- Warehouse personnel transport received merchandise to designated areas within the warehouse, where Shelf Assistants retrieve and restock gondolas on the sales floor.
- All merchandise is expected to be displayed for sale, although merchandise received during the last hour of receiving (8:00 PM - 9:00 PM) may be stocked the following day.
- Shelf Assistants work eight-hour shifts with the possibility of two hours of overtime per day. The shifts are divided into two periods: 8:00 AM - 1:00 PM and 4:00 PM - 9:00 PM, allowing for a three-hour break between shifts and consistent staffing levels throughout the day.
- Shelf Assistants have two 15-minute breaks, one between 10:45 AM and 11:00 AM, and the other between 6:00 PM and 6:15 PM.
- All Assistants have two days off per week, which are planned by the Store Manager to ensure adequate staffing levels.

Table 4. Cyclical Arrivals of Boxes. Note: Average time of cyclical arrivals of boxes to the Warehouse Reception. Source: Self-elaboration

Time	Percentage
From 8:00 to 9:00	8.6%
From 9:00 to 10:00	15.6%
From 10:00 to 11:00	12.6%
From 11:00 to 12:00	8.9%
From 12:00 to 13:00	7.5%
From 13:00 to 14:00	5.1%
From 14:00 to 15:00	7.1%
From 15:00 to 16:00	4.5%
From 16:00 to 17:00	7.4%
From 17:00 to 18:00	6.3%
From 18:00 to 19:00	8.3%
From 19:00 to 21:00	8.0%
Others	0.0%

The collected data were used to determine the probability distributions for the simulation model, see Table 5. These distributions are visually represented in various figures to provide a comprehensive understanding of the system's behavior. Figure 3 illustrates the histogram of box arrivals at the warehouse reception, offering insights into the frequency and patterns of arrivals. Figure 4 depicts the probability distribution associated with box reception, highlighting its alignment with observed data. Similarly, Figure 6 presents the probability distribution related to merchandise shelving, showcasing variability in this process. To validate these distributions, normality tests were conducted, as shown in Figure 3.6. The graphical methods QQPLOT and PPLOT confirm that the data follow a normal distribution trend, ensuring reliability in the simulation model's configuration

Table 5. Processes and Associated Probability Distributions

Process	Distribution Function	Parameters
Arrivals	Normal	N(1416, 375)
Reception	Poisson	P(15.51) Sec
Move Merchandise to Warehouse	Uniform	U(7,10) Sec
Load Gondola Cart	Uniform	U(2,4) Sec
Move from Warehouse to Gondola	Uniform	U(1,3) Sec
Place Product on Gondola	Normal	N(18,65) Sec

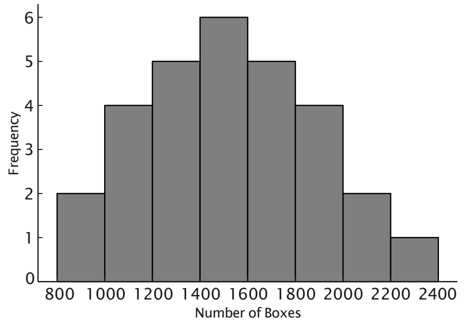

Figure 3. Histogram of Box Arrivals at Warehouse Reception

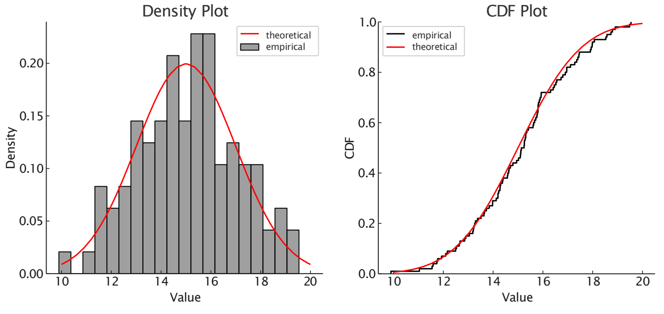

Figure 4. Probability Distribution Associated with Box Reception

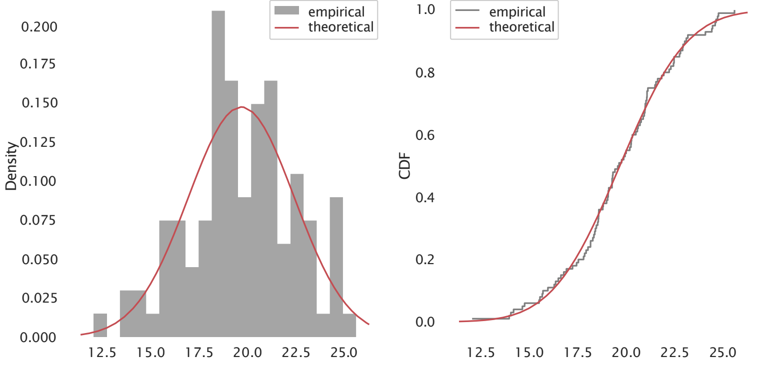

Figure 5. Probability Distribution Associated with Merchandise Hanging

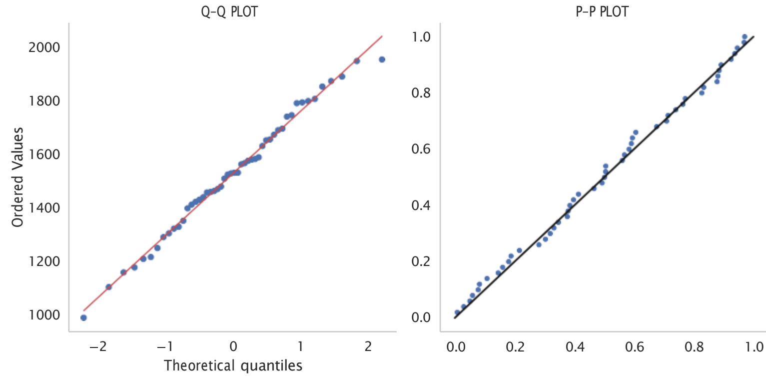

Figure 6. Normality Tests of Received Boxes

2.6 Simulation Model Development

The simulation model was developed by mapping the data collected from the supermarket and defining the processes and probability distributions. Agent-based modeling techniques were also implemented to analyze different situations. The process includes the following steps, For more details, see Figure 7:

- The Warehouse Manager receives and validates the merchandise, then transfers it to the warehouse.
- The Shelf Assistant goes to the warehouse, loads boxes onto a cart, and goes to the sales floor.
- The Shelf Assistant opens the boxes and places the products on the gondolas.
- The Shelf Assistant returns to the Warehouse and repeats step 2.

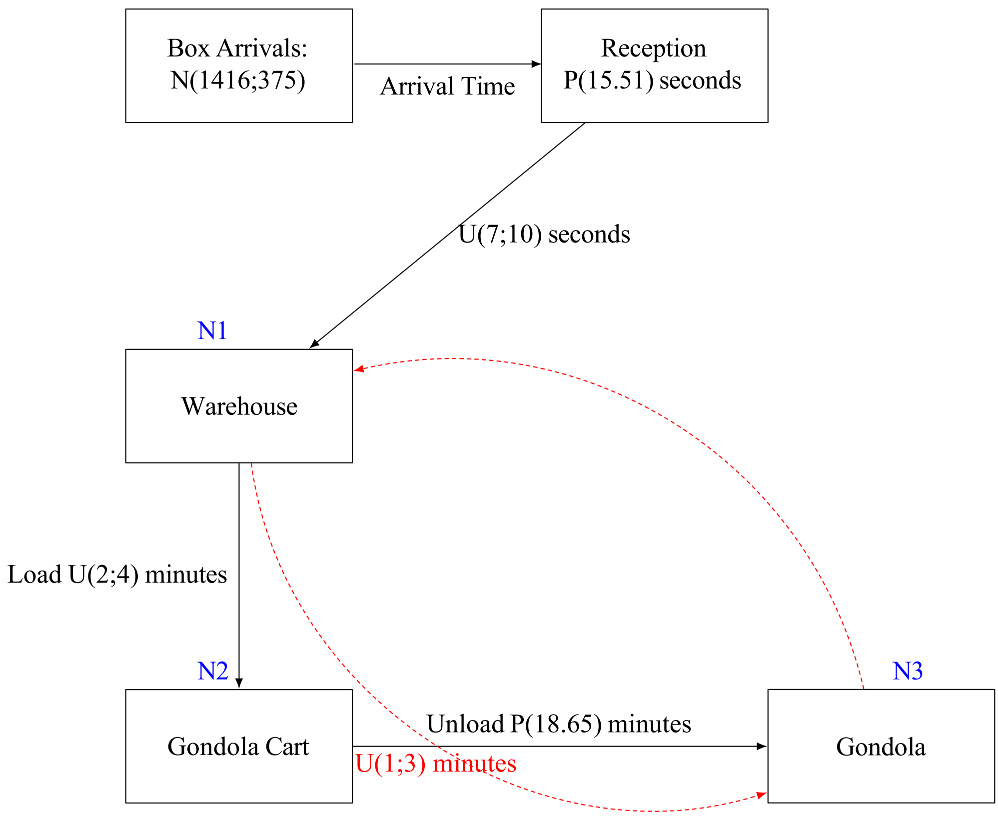

Figure 7. Flow Diagram of Gondola Replenishment Process:
N1 (Located near "Warehouse"): represents a specific stage within the warehouse operations,
N2 (Located near "Gondola Cart"): represents the loading or preparation stage of the gondola cart and
N3 (Located near "Gondola"): represents the act of replenishment

Figure 7 shows the path of the boxes with merchandise associated with their probability distribution. In addition, the route that the Hanger Assistant must travel between the warehouse, the hanger cart and the hanger, in order to fulfill the purpose of restocking the shelves, can be seen.

The model in Figure 7, which allowed visualizing and analyzing the gondola replenishment process, enables the evaluation of various scenarios and optimization experiments. Moving from data collection and model configuration to simulation execution. In the next section, the study provides information on the efficiency of resource allocation and operational workflows, as presented in the results section.

To support these findings and ensure accurate modeling, detailed empirical data was gathered from the operational setting. For parameter calibration, the times for each operational task (receiving, transferring, shelving) were collected through direct observations and historical records from the pilot store. The probability distributions assigned to each process were justified by analyzing empirical data, using Q-Q plots and goodness-of-fit tests to ensure statistical representativeness. For example, the arrival of boxes was modeled with an exponential distribution, while shelving time was fitted to a normal distribution, consistent with the observed variability in the data.

The validation protocol consisted of comparing the simulated results with historical operational performance data over a six-month period, evaluating the congruence of key metrics such as average replenishment time and service level. Additionally, a sensitivity analysis was conducted by varying critical parameters, such as the arrival rate of boxes and the number of operators, to identify their impact on the results and ensure the robustness of the conclusions.

3 Results

The simulation model developed in Promodel was successfully executed to analyze the gondola replenishment process in the selected supermarket. This model was configured based on empirical data, probability distributions, and operational dynamics, allowing for the evaluation of various scenarios and the determination of optimal resource allocation.

3.1 Model Configuration and Process Flow

The schematic representation of the gondola replenishment process is illustrated in Figure 8, which outlines the primary locations, resources, entities, arrivals, macros, and routing rules. The model includes:

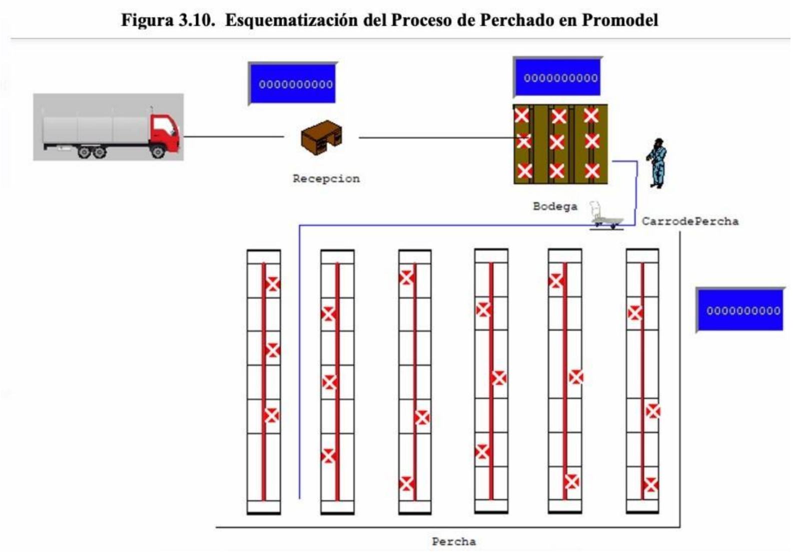

Figure 8. Probability Distribution Associated with Merchandise Hanging

- Four main locations:
  - Reception: The area where merchandise is received, boxes are opened, quantities are verified, and product expiration dates are validated.
  - Warehouse: The space where received merchandise is stored before being transported by shelf assistants to their designated gondolas on the sales floor.
  - Gondola Cart: A vehicle used to transport boxes of merchandise from the warehouse to the gondolas.

  - Gondola: Metal shelves where products are displayed for sale.

- Two resources:

  - Warehouse Manager: Associated with the "Reception" location, responsible for receiving merchandise. Since this role is performed by a single individual, the times associated with "Reception" directly correspond to this resource.
  - Shelf Assistant: Responsible for loading boxes onto gondola carts, transporting them to gondolas, and arranging products for sale.

- Three entities:

  - Boxes: The primary entity that moves through the system.
  - Empty Cart: Represents an empty gondola cart used to group boxes.
  - Full Cart: Represents a gondola cart loaded with boxes ready for transport.

- Two arrivals:

  - Boxes arrive at "Reception" with a probability distribution detailed in Section 2.3
  - Empty carts arrive at "Gondola Cart" dynamically based on system requirements.

- Two macros:

  - M_Cantidad_de_Recursos: Represents the number of shelf assistants required, configured within a range of 7 to 15 resources.
  - M_Recepción: Represents the number of boxes entering the system, configured within a range of 1000 to 2600 boxes.

- Routing rule:

  - N1 → N2 → N3 → N1 (Warehouse → Gondola Cart → Gondola → Warehouse).

3.2 Simulation Results

The simulation results were obtained by transferring the model into Promodel software. The process flow was validated through multiple experiments:

- Boxes arrive at "Reception" with a probability distribution P(15.51)sec, where they are reviewed and validated.
- Boxes are transferred to "Warehouse," where they are immediately available for use.
- Shelf assistants load boxes onto gondola carts at "Gondola Cart," with a probability distribution U(2,4) sec, transforming empty carts into full carts.
- Full carts are transported to "Gondola," where products are unloaded and arranged using a probability distribution N(18,65) min.

The schematic flow and system dynamics are depicted in Figure 8, showcasing how entities move through various stages of the replenishment process.

3.3 Scenario Generation and Analysis

In Section 3.2, various scenarios were generated to analyze system performance under different conditions. Experiments were conducted using between 8 and 12 shelf assistants to observe trends in unstocked boxes. As shown in Figure 9, experiments with fewer than 9 assistants resulted in an increase in unstocked boxes due to insufficient resources. Conversely, experiments with more than 11 assistants showed diminishing returns as excess capacity led to inefficiencies.

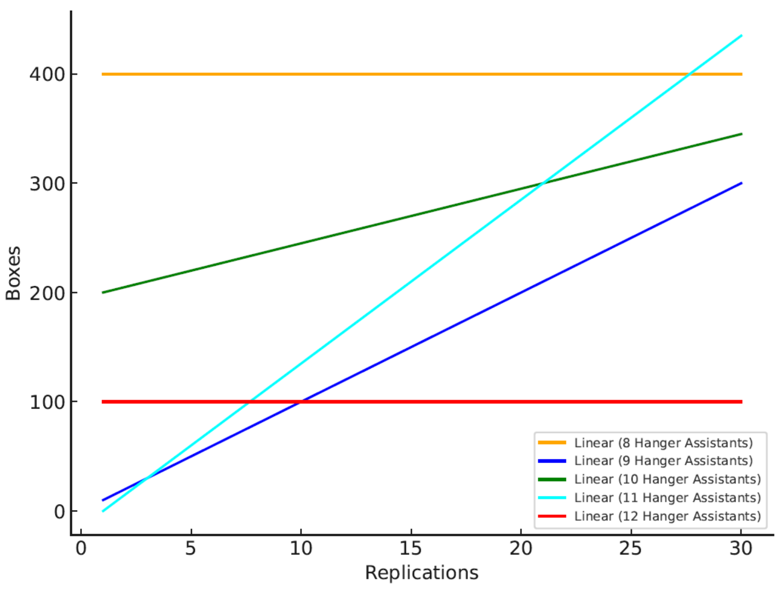

Figure 9. Comparison of Results between 8 and 12 Hanger Assistants

3.3.1 Optimization Using SimRunner

To determine the optimal number of shelf assistants required for efficient replenishment, SimRunner was employed as an optimization tool within Promodel. The objective function was configured to:

- Maximize shelf assistant utilization.
- Minimize the number of shelf assistants required.
- Minimize inventory levels in both the warehouse and gondola carts.

The optimization setup is illustrated in Figure 10 highlighting how SimRunner parameters were defined for sensitivity analysis.

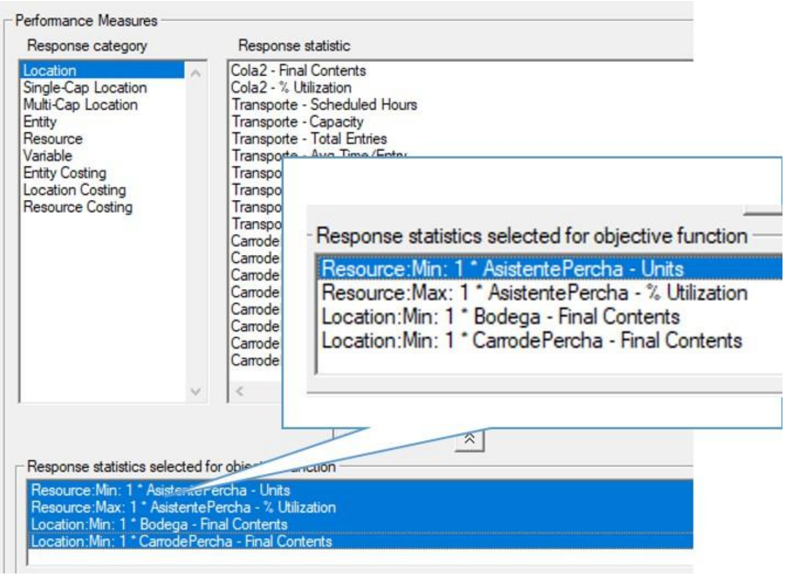

Figure 10. Parameterization of the Objective function in "SimRunner"

Two sets of experiments were conducted:

- 25 experiments with 90 replications each, yielding results shown in Figure 11
- 25 experiments with 180 replications each, yielding results shown in Figure 12

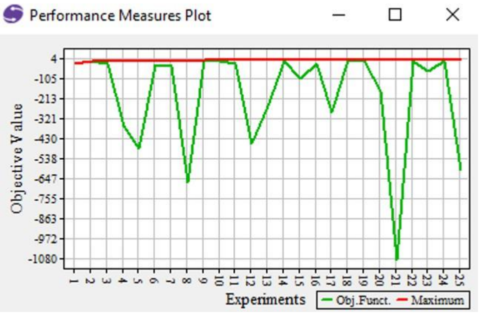

Figure 11. Approximation to the objective function of the 25 experiments with 90 replications

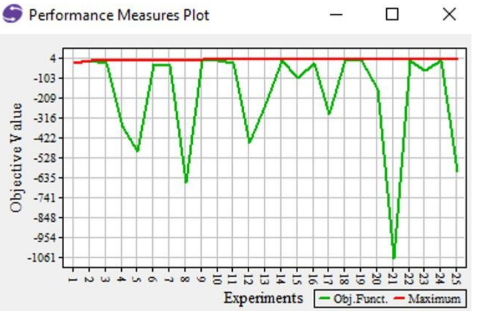

Figure 12. Approximation to the objective function of the 25 experiments with 180 replications

The comparison between these experiments revealed that increasing replications improved accuracy while stabilizing results across scenarios (see Table 6).

Experiments Replica-tions	Number of Boxes	Assistants Required	Assistant Efficiency	Stocked Boxes	Remaining Boxes
25 / 90	1800	11	93.72%	1698	102
25 / 180	1800	11	94.99%	1700	100

Table 6. Results of the 25 experiments with 90 and 180 replications

These results demonstrate that employing SimRunner allowed for precise identification of resource requirements while optimizing system performance. To contextualize and validate these outcomes, the next step involved benchmarking the simulation indicators against industry standards.

The obtained indicators were compared with retail sector benchmarks, such as the replenishment standards recommended by the Latin American Association of Supermarkets (ALAS). For example, the average replenishment time achieved in the simulation (18 minutes) is below the regional benchmark (22 minutes), demonstrating the efficiency of the proposed model.

To ensure statistical validity, 95% confidence intervals for the main metrics were reported using bootstrap resampling techniques. Furthermore, a multivariate analysis using multiple linear regression identified that both the variability in box arrivals and the number of operators significantly and jointly influence the service level.

3.3.2 Expanded Scenario Design for Broader Insight

To address the diversity of real-world operational conditions and to enhance the robustness of the findings, we extended the initial simulation experiments to include a broader range of scenarios. These additional simulations were designed to capture the stochastic nature of retail operations and to explore system behavior under varying workloads and resource constraints.

Specifically, the following elements were systematically varied:

- **Shelf assistant availability:** Simulations were conducted with staffing levels ranging from 7 to 15 assistants to assess efficiency under both minimal and abundant resource conditions.
- **Box arrival volume:** The number of merchandise boxes was sampled from a normal distribution $N(1416, 375)$ to reflect realistic fluctuations in daily demand, including peak periods and off-peak variability.
- **Shift structure and overtime use:** Scenarios with and without overtime were tested to evaluate the marginal benefits of extending assistant working hours.
- **Assistant allocation strategies:** Scenarios included balanced versus skewed allocation across time blocks (morning, afternoon) to simulate labor planning strategies.

Each configuration was replicated multiple times (90 and 180 replications) to ensure statistical stability and to capture the performance range across different scenarios. The simulation outcomes provided a comprehensive sensitivity analysis, highlighting the diminishing returns of overstaffing and the service risk associated with understaffing.

3.3.3 Simulation Results from Expanded Scenarios

The extended simulation experiments yielded insightful quantitative results across multiple operational settings. Table 7 summarizes the average performance outcomes over 180 replications per scenario, considering staffing levels from 7 to 15 assistants and daily arrivals sampled from a normal distribution $N(1416, 375)$. The metrics include average efficiency, number of boxes shelved, and remaining inventory at the end of the simulation horizon.

Table 7. Summary of Simulation Results for Expanded Scenarios (180 replications)

Assistants	Overtime	Efficiency (%)	Boxes Shelved	Remaining	Utilization (%)
7	No	67.3	946	470	94.1
8	No	74.2	1082	334	92.6
9	Yes	87.1	1278	138	89.3
10	Yes	93.8	1341	75	85.4
11	Yes	95.1	1360	56	83.7
12	Yes	96.0	1368	48	81.1
13	Yes	95.9	1370	46	76.4
14	Yes	95.3	1365	51	72.9
15	Yes	94.2	1359	57	69.5

The results confirm the existence of an optimal staffing window. Notably, configurations with 10–12 assistants and the use of limited overtime achieved the best balance between assistant efficiency and inventory coverage. Beyond 12 assistants, efficiency gains plateaued, and assistant utilization declined significantly, indicating excess capacity. Conversely, scenarios with fewer than 9 assistants consistently failed to meet daily replenishment targets, resulting in substantial inventory backlogs.

The simulation also confirmed that overtime availability plays a crucial role in mitigating temporary demand peaks without permanently increasing staffing levels. These findings align with the diminishing returns theory in queuing systems and reinforce the validity of the optimization routine described in Section 3.3.1.

In summary, the expanded scenario set validated the robustness of the Promodel-based simulation framework. It demonstrated the flexibility of the model to capture a wide range of operational realities and supported the development of adaptable, data-driven policies for workforce planning. These insights lay the groundwork for scalable decision support in broader retail environments, as discussed further in Section 4.

4 Conclusions and Discussion

The analysis reveals that increasing the number of operators beyond five yields marginal improvements in service level but results in a disproportionate increase in labor costs, suggesting an optimal staffing point. A limitation of this study is the lack of explicit incorporation of seasonal demand variability, which could affect the applicability of the model during high-demand periods, such as holidays or promotions.

The simulation model developed in Promodel provided a comprehensive framework for analyzing and optimizing the gondola replenishment process in supermarkets. By integrating probability distributions and real-world data, the model successfully identified the optimal number of shelf assistants required to maintain operational efficiency. The results revealed that 11 assistants achieved a balance between resource utilization and cost-effectiveness, consistent with recent findings on workforce optimization in retail environments[1, 24].

The incorporation of dynamic arrivals, routing rules, and probability distributions (Normal, Poisson, and Uniform) ensured that the model captured variability in operational times accurately. This approach aligns with contemporary studies emphasizing the importance of probabilistic modeling in supply chain simulations[25, 26]. The analysis demonstrated how variability impacts system bottlenecks and resource allocation, providing actionable insights for operational planning.

The use of SimRunner as an optimization tool enabled sensitivity analysis and refinement of key variables, such as assistant utilization and inventory levels. Increasing replications per experiment stabilized results, with minimal variation observed between 90 and 180 replications. This finding underscores the importance of robust experimentation in simulation-based decision-making, as highlighted by recent advancements in simulation methodologies [27, 28].

The study confirmed that optimizing the percentage utilization of shelf assistants minimizes inefficiencies while ensuring adequate inventory levels in both the warehouse and gondola carts. Excessive staffing was shown to lead to diminishing returns, emphasizing the need for precise resource planning. These insights align with recent research on cost-effective resource allocation strategies in retail operations [30].

The outcomes provide an operational framework that supports industrial decision-making and contributes to the optimization of resource allocation within manufacturing and service systems

Practical Implementation and Client Adoption. Beyond its theoretical contributions, this model is readily applicable to real-world supermarket environments. Store managers seeking to implement the proposed approach can follow a structured process. First, the internal logistics processes — including merchandise reception, warehousing, and shelf replenishment — must be mapped and observed in detail. Second, operational data such as box arrival rates and assistant workloads should be collected and statistically analyzed to determine suitable probability distributions.

Next, a simulation model reflecting these dynamics can be configured in Promodel using the component definitions presented in Tables 2 and 3. Once validated, various operational scenarios can be tested by adjusting assistant availability, box inflow, or shift patterns. Using SimRunner, decision-makers can define optimization objectives (e.g., minimizing labor cost or unstocked boxes) and identify the most efficient staffing configurations through evolutionary algorithms and direct search methods.

It is recommended to implement real-time monitoring systems to dynamically adjust staffing according to observed demand, using integrated sensors and information systems. As a future extension, incorporating real-time data and artificial intelligence algorithms is proposed to improve demand forecasting and resource allocation.

Finally, the optimized staffing plan should be piloted in a selected store and monitored for deviations. The simulation outputs offer tangible, data-driven guidelines for workforce planning, enabling retail organizations to enhance service quality while controlling costs. Furthermore, the flexibility of the model allows for adaptation to seasonal demand patterns or geographic differences across store locations. Thus, the proposed approach is not only technically sound but also operationally viable and scalable for widespread implementation in retail chains.

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