Integration of Monte Carlo Simulation and Linear Programming in Multi-Product Multi-Stage Supply Chains: A Theoretical Framework for Decision-Making under Uncertainty

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ABSTRACT

This study outlines a hybrid Monte Carlo Simulation-Linear Programming framework to increase the level of operational efficiency of a multi-stage supply chain. This model is an integration of probabilistic simulation and deterministic optimization to take into account the effects of demand variability, lead-time variability, and capacity variability on profitability and the overall service delivery performance. The suggested framework is tested with the help of a multi-product, multi-stage supply chain case study that is implemented on the basis of a publicly available dataset containing around 9000 transactional records. Monte Carlo simulation generates random uncertainty scenarios, whereas linear programming finds the ideal decisions related to production, distribution, and inventory levels for each iteration. The results suggest that reducing the amount of demand variability and better capacity planning resulted in a good performance with an expected profit of \$328,100.16, a profit variance of 3.72×10^9, and a service level of 94.3%. The result of the sensitivity analysis shows that demand variability and lead times have a negative effect on profit, while optimal capacity planning enhances operational flexibility. The MCS-LP provides an advantage to the use of stochastic and deterministic methods for risk-aware decision making and has the potential to be computationally scalable and efficient for uncertainty-driven supply chain design. The general approach provides a decision-support tool for managers considering how to balance costs, risk, service quality, and uncertainty in ever-changing industrial contexts.

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1 Introduction

In the present-day economy of globalization, supply chain management is critical to ensuring the seamless movement of materials, products, and information from its sources to the end-consumer [1]. With the growing complexity of multi-stage, multi-product supply networks, decision-making has become increasingly challenging [2]. Companies must be able to plan production, control inventories, transportation, and distribution well to keep up with the competition [3]. Supply chain optimization reduces operational cost [4] and eventually enhances customer demands and market responsiveness that are vital to the long-term sustainability of the supply chain.

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Despite technological development, supply chains have continued to be faced with significant uncertainties brought by the fluctuation in customer demand, lead time fluctuation, and disruptions brought about by market, environmental, or other disruptions [5]. Fluctuating production capacity, variability of supply, unpredictability of transportation [6], and unexpected international phenomena, including pandemics or a war, can pose a significant threat to supply chain performance [7]. Thus, these uncertainties need to be managed and resolved to enhance the accuracy of decisions and to provide resiliency at any point of the supply chain [8].

Traditional optimization techniques, such as deterministic Linear Programming (LP) and simulation-based approaches, have been widely applied in enhancing efficiency in supply chains [9]. Deterministic LP provides a structured mathematical-based approach to optimizing decisions regarding production and distribution [10], given that the conditions are fixed, but it often fails to reflect the randomness of real-world situations [11]. Simulation methods, including Discrete Event Simulation and System Dynamics, allow modeling of uncertainty, but do not analyze optimization [12]. Consequently, a mix of previous techniques has either optimized choices without modeling uncertainty [13].

Although the integration of optimization and uncertainty modeling has been explored in previous supply chain studies, many existing approaches rely on complex multi-stage stochastic programming formulations or tightly coupled simulation–optimization frameworks that require explicit scenario trees, which can become computationally intensive and difficult to interpret for large-scale, multi-product, multi-stage supply chains. In contrast, the proposed Monte Carlo Simulation–Linear Programming (MCS–LP) framework adopts a decoupled structure in which uncertainty is represented through flexible Monte Carlo sampling, while optimization is carried out using deterministic linear programming for each realization. This structure enables scalable and transparent evaluation of expected profit, profit variance, and service level, thereby providing a risk-aware and managerially interpretable decision-support tool for supply chain planning under uncertainty. The main contributions of this research are as follows:

- ❖ Coupling suggests a decoupled MCS-LP model that would incorporate modelling of uncertainty and optimization without explicit stochastic scenario trees.
- ❖ Presents profit variance as a major risk measure along with anticipated profit and service level within multi-product, multi-stage supply chains.
- ❖ Gives a quantitative study of the trade-off between capacity flexibility and profit variability using Monte Carlo sensitivity analysis.
- ❖ Embarked on the expected profit, profit variance, and service level as two of the expected performance measures to measure the financial outcomes and operational stability.
- ❖ To make decisions on the planning of production and cost-risk management, deliver a data-driven and scalable decision support model that can be exercised on the actual supply chains in the real world.

Although stochastic programming and robust optimization are proven methods to deal with uncertainty in supply chain optimization, they may need explicit scenario trees, known probability distributions, or worst-case uncertainty sets, which are computationally infeasible in large-scale multi-product, multi-stage systems. By contrast, the hybrid Monte Carlo Simulation-Linear Programming (MCS-LP) framework proposed enables the uncertainty to be sampled in a flexible way without the necessity to explicitly enumerate the scenarios and use the worst-case assumptions. This methodology allows the risk profiling of risks, assessing their variability in profits, and the analysis of services at the level of detail, with the preservation of the computational simplicity and transparency of linear programming. Therefore, MCS-LP is especially applicable in information-based decision support in complex supply networks where uncertainty is significant, the distributions are non-perfectly known, and the interpretability desired by managers.

Research Hypothesis

In contemporary supply chains, the operational flexibility is an important balance, especially in the form of effective capacity planning, to deal with uncertainty and the facilitation of the operations. But supply chains are generally in a complicated trade off between providing greater operational flexibility (through capacity) and ensuring profit stability. Although the issue of capacity planning is likely to reduce the effects of the variability in demand and lead time uncertainty; it is also prone to causing the operation costs to rise thereby increasing the profit variance.

This research paper will be based on the hypothesis that capacity planning (operational flexibility) and profit variance are trade-off in multi-stage supply chains. Particularly, one of the hypotheses is: Hypothesis 1: There will be an initial reduction in profit variance as the capacity flexibility will address the influence of demand and lead time uncertainty. But beyond a given point, it is clear that the capacity cannot be increased further flexibility will result in a greater profit variance because of higher operating costs that will be incurred as a result of excess capacity. This hypothesis will be tested by analysing the results from a Monte Carlo Simulation and Linear Programming model, where capacity planning decisions are varied and their effects on profit variance are observed.

The remainder of this document is structured as follows: Section 2 reviews the relevant literature regarding stochastic optimization and simulation-based supply chain models. Section 3 describes the proposed MCS–LP method and describes the workflow. Section 4 and Section 5 provides information regarding the experimental setup and the sensitivity analysis with performance as one of the considerations. Section 6 presents the results with relevant interpretations. Finally, Section 7 summarizes the work with concluding details and opportunities for future investigation.

2 Literature Review

Ehichoya and Osagiede [14] proposed a stochastic decision-making model of closed-loop supply chain networks to attain sustainability based on a scenario setting. Their model has tackled the trade-off between environmental and economic goals whereby uncertainty modeling has been of significance in product returns and recycling. Katsavounis and Koutsokosta [15] explored stochastic extensions of the mixed-integer program models in the construction supply chain. They presented the benefits of stochastic optimization in enhancing robustness in planning during probabilistic conditions based on the application of chance-constrained and two-stage programming.

Chen and Zhang [16] examined a multi-period, multi-product, stochastic inventory model, which incorporated the financial considerations including order-based loans. They used their study to make a point about how financial uncertainty and stochastic demand influence the optimal ordering and replenishment policy. Bhowmik and Parvez [17] utilized Mixed Integer Linear Programming (MILP) and Monte Carlo Simulation to develop an optimal supply chain network. The combination of the two strategies in minimizing costs and capturing demand uncertainty was effective, and thus, has had an almost similar methodological direction as the current research paper. Benfer et al. [18] suggested a stochastic optimization model of dual-perspective capacity planning in multi-product production networks. The results of their study pointed to the importance of stochastic modelling in decisions in interdependent systems with variable demand in production.

The proposed blockchain-based vaccine supply chain model by Shiri et al. [19] dealt with hybrid uncertainties with stochastic optimization. Their methodology showed that the use of new technologies and probabilistic modeling can increase the transparency and resilience in important logistics systems. Xu and Song [20] came up with an integrated production capacity and raw material planning optimization model under the uncertainty of time and quantity. They demonstrated a great enhancement in efficiency and adaptability in uncertain environments by using their model on real-life case studies. Rezaei and Qiong [21] developed an effective supply chain network that focuses on the robust selection of suppliers in the case of a disaster. Their study led to the recognition of the balance of robustness and resilience with the help of strategic sourcing and stochastic design.

Dehghani Sadrabadi et al. [22] developed a combined optimization model of supply chain maintenance and resiliency during supply chain disruptions that are interrelated. Their case study validated the significance of optimization-based frameworks in the management of systemic risks and stability in operations. Momenitabar et al. [23] came up with an efficient possibilistic programming model in the design of an integrated blood supply chain network as a closed loop. Their solution aimed at maximizing the level of services, and the optimization of lateral resupply strategies in the presence of uncertain and imprecise conditions, demonstrating the usefulness of uncertainty-conscious optimization in humanitarian logistics.

Simulation–optimization approaches have been widely applied to address uncertainty in supply chain decision-making. For instance, Shadkam and Bijari [24] proposed a multi-objective simulation–optimization model for supplier selection and order quantity determination under uncertainty. Similarly, Shadkam et al. [25] introduced a hybrid stochastic optimization algorithm for integrated production–distribution planning problems. More recently, Jafarzadeh Ghoushchi et al. [26] developed a robust multi-objective optimization framework for multi-stage, multi-product supply chains in the context of circular economy. In addition, Rostamzadeh et al. [27] addressed uncertainty in multi-product, multi-period sustainable supply chain optimization with a focus on perishable products.

Although stochastic programming and simulation–optimization methods have been widely applied to supply chain planning under uncertainty, several limitations remain. Existing stochastic programming models often rely on explicit multi-stage scenario trees that grow exponentially with problem size, thereby limiting scalability in multi-product, multi-stage systems, while simulation–optimization approaches typically emphasize cost minimization or network resilience with limited attention to profit variance and service-level stability as joint performance outcomes.

2.1 Research Gap

Although supply chain optimization under uncertainty has been widely studied using stochastic programming, robust optimization, and simulation optimization methods, these approaches often face limitations related to scalability, excessive conservatism, and limited risk interpretation. The existing Monte Carlo-based literature is largely based on cost or network structure and does not typically quantify profit variability or examine service level as an emergent outcome of optimization and the trade-off between capacity flexibility and profit variance has not been understood very well. This study fills these gaps by introducing a Monte Carlo Simulation Linear Programming (MCS–LP) model, which decouples uncertainty modelling and optimisation and analyses expected profit, profit variance, and service level, offering a scalable, risk-sensitive and managerially interpretable multi-product multi-stage supply chain decision-support model.

2.2 Problem Statement

In this work, a multi stage supply chain is forward, multi-product and runs on a finite planning horizon in the presence of uncertainty in the customer demand, supply lead times, production capacity and the cost parameters [28]. Stochastic variability in the parameters is modeled using historical transactional data, which is used to determine baseline values, and modeled by using predefined probability distribution and Monte Carlo Simulation [29,30]. The decision problem is to solve how to pick the best levels of production, stock, and transportation flow of each product and production stage, while production and transportation capacity limits, inventory balance relations, non-negativity constraints, and obligatory demand fulfillment without stockout [31]. The production, inventory holding and transportation activities are assumed to be linear in cost [32]. It aims to maximize the expected profit by analyzing the performance of the variability of profits and the level of service by considering the variability of the profit in each Monte Carlo realization and optimizing the Linear Programming model chosen, thus allowing risk-sensitive and consistent operations decisions in the multi-product and multi-stage supply chain [33].

Stochastic programming relies on multi-stage scenario trees that grow exponentially with the number of uncertain parameters, leading to high computational complexity. Robust optimization focuses on worst-case feasibility, which often results in overly conservative and less profitable solutions. The proposed MCS–LP framework decouples uncertainty modeling from optimization, enabling scalable, interpretable analysis of profit, risk, and service performance under uncertainty.

3 Proposed Methodology

The suggested Fig. 1 provides an explanation of how MCS-LP are integrated to optimize supply chain in the conditions of uncertainty. The process starts with the collection of data and parameterization when the baseline values of the demand, cost, capacity, and lead time are set. Monte Carlo Simulation module develops randomization of these uncertain parameters through the probabilistic distributions to imitate the variability of the real world. All the simulated scenarios are then analyzed using the Linear Programming Optimization model to find out the best production, inventory and distribution decisions that will result in a minimum total cost or a maximum total profit. The outputs of the several simulation runs are combined in the Result Aggregation stage to calculate the key performance indicators which include expected profit, profit variance, and service level. Lastly, Sensitivity Analysis assesses the impact of changes in demand, capacity, and lead time on profitability and operation efficiency and offers useful information in strategic decision-making in supply chains.

3.1 Dataset Description

This study utilized a dataset obtained from the public Supply Chain Dataset available on Kaggle that contains a complete record of transactional and operational data regarding supply chain networks that contain multiple products and multiple stages. The dataset has numerous characteristics describing the supplier's performance, the product category, shipment details, warehouse and storage characteristics, and customer orders Notably, the dataset is a practical benchmark to the modeling of production planning, inventory management and transportation decision-making problems with uncertain demand and cost conditions and has a direct relationship with the objectives of the study [34].

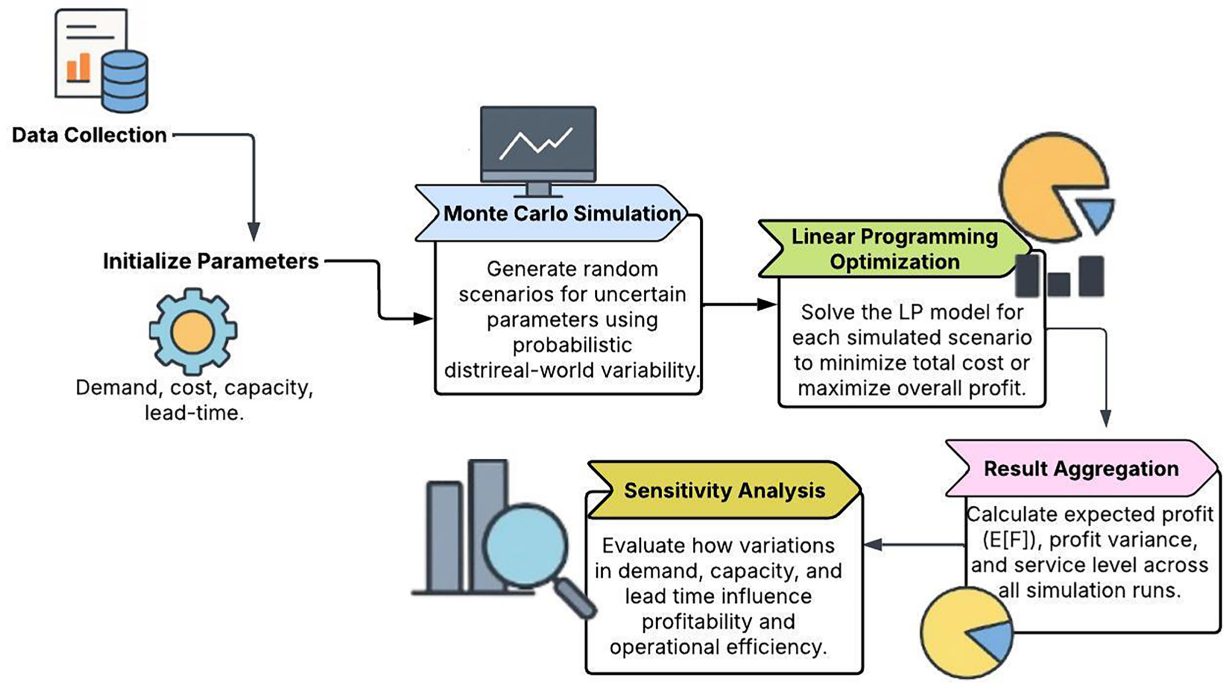

Figure 1: Proposed workflow of the Monte Carlo Simulation-Linear Programming (MCS-LP) framework

In order to calculate the performance of the proposed MCS-LP model, the dataset was separated into training and test sets as shown in Table 1 below. Running of Monte Carlo simulations and the linear programming optimization problem were applied to the training set and the test set was limited to checking the robustness and generalizability of the model results. Even though the MCS-LP model is deterministic (i.e., it yields the same answer with a given set of inputs) with the addition of uncertainty by Monte Carlo simulations, the validation is necessary to ensure that the results are not overfitted to the training data and can be generalized to new, previously unknown data. The segmentation of the dataset into these subsets ensured that the model predictions of the key performance metrics, including anticipated profit and service level would be reliable and robust in response to the varied data conditions in the context of stochastic variability.

- **Data Set Division:** 80 percent of data was utilized in training the models and 20 percent was utilized in testing and validating the simulation outcomes.
- **Data Volume:** There are approximately 9000 transactional records of various levels of the supply chain and products of various varieties.
- **Data Source:** The data was copied in both synthetic and real-world-based business process simulation that was based on supplier-to-customer cases, which were varied and dynamic operation cases and offered the low of variability as a way of uncertainty modeling.

Table 1: Feature types used in supply chain modeling and their descriptions

Feature type	Example features	Description
Product information	Product type, Category, Unit price, Cost, Profit	Represents basic product-level attributes used for computing production and sales revenue across different stages.
Supplier and procurement	Supplier name, Supplier rating, Lead time, Purchase cost	Describes supplier performance and procurement delays, influencing upstream supply chain uncertainty.
Inventory and logistics	Warehouse ID, Stock levels, Shipping mode, Transportation cost	Captures inventory movement, logistics decisions, and transportation costs across supply chain stages.
Demand and sales	Order quantity, Customer region, Demand frequency, Sales revenue	Reflects fluctuating customer demand and regional market variations used for uncertainty modeling in Monte Carlo Simulation.
Temporal attributes	Date, Month, Delivery time	Provides chronological context for time-based performance tracking and multi-period decision-making.

Uncertainty Representation and Probability Distributions

To simulate the uncertainty of the supply chain parameters, apply Monte Carlo Simulation (MCS) to obtain random samples of each uncertain parameter, which are demand, lead time, and capacity that are important in assessing supply chain functionality to different conditions. MCS allows simulating a very diverse range of scenario with stochastic variations in these parameters to give a very robust analysis of the behaviour of the supply chain. The chosen probability distributions on each parameter use historical, industry standard, and expert judgment to take realistic variability on the supply chain operations. The distributions are employed to model the uncertainty in the model and assesses how it will affect the performance measures like cost, service, and profitability.

Table 2 illustrates the distribution of each parameter, which was decided on to represent the uncertainty in the supply chain in the real world. Demand is normally distributed to show normal changes and lead time is based on Triangular distribution with known limits. Capacity is modeled under Uniform distribution which means even distribution of minimum and maximum values. The production cost is Lognormally distributed to explain skewed cost structure, and transportation cost is Triangularly distributed to explain logistics variability. Sampling of these distributions in each Monte Carlo Simulation iteration is done and the Linear Programming model is used to optimize production, inventory and distribution decisions. The outcomes of the various simulations are summarised together to give a holistic picture on the supply chain performance in case of uncertainty.

Table 2: Probability distributions of uncertain parameters.

Parameter	Probability distribution	Mean	Standard deviation	Range/Support
Demand	Normal ($\mu = 500$, $\sigma = 50$)	500 units	50 units	[300, 700] units
Lead time	Triangular (a = 2, b = 4, c = 6)	4 days	1 day	[2, 6] days
Capacity	Uniform (min = 4000, max = 6000)	5000 units	N/A	[4000, 6000] units
Production cost	Lognormal ($\mu = 5$, $\sigma = 0.3$)	$5	$0.5	[3.5, 7.5] USD
Transportation cost	Triangular (a = 1, b = 2, c = 3)	$2	$0.5	[1, 3] USD

Note: N/A, Not Applicable.

3.2 Model Description

A. Assumptions of the Model

The mathematical model for the formulated multi-product, multi-stage supply chain optimization framework with MCS and LP is based on the following assumptions:

- ❖ The average period demand of each product is uncertain and modelled by Monte Carlo Simulation.
- ❖ Raw materials will be fully available throughout the planning horizon.
- ❖ The supply chain includes products and multiple operational stages.
- ❖ The system is a single-objective optimization model that maximizes expected profit.
- ❖ The planning horizon is finite, consisting of a discrete number of periods.
- ❖ All customer demand is satisfied in each scenario; physical stockouts are not permitted, although higher operational costs may be incurred under adverse conditions.
- ❖ Unit production cost is known and constant in each stage.
- ❖ Unit inventory holding costs are fixed and an estimation of holding costs are constant across all periods.

B. Model Notations

The notation of the model defines the main variables and parameters used to characterize decisions for production tabulated in Table 3 below, inventory, and transportation within the suggested MCS–LP framework. It provides the mathematical foundation linking cost, demand, and capacity across multiple products and stages. This representation is systematic and clear and it facilitates an appropriate integration of uncertainty through the Monte Carlo Simulation.

Table 3: Mathematical notation for supply chain optimization model

Symbol	Description
i	Index for products ($i = 1, 2, \ldots, I$).
j	Index for supply chain stages ($j = 1, 2, \ldots, J$).
p	Index for planning periods ($p = 1, 2, \ldots, P$).
t	Index for Monte Carlo simulation trials ($t = 1, 2, \ldots, T$).
u_{ijpt}	Production quantity of product i at stage j in period p during trial t.
x_{ijpt}	Inventory level of product i at stage j in period p during trial t.
y_{ijpt}	Quantity of product i transported from stage j to $j+1$ in period p.
d_{ijpt}	Demand for product i at stage j during period p in trial t.
R_{ijpt}	Revenue obtained from selling product i at stage j during period p.
C_{ijpt}^{prod}	Unit production cost of product i at stage j in period p.
C_{ijpt}^{inv}	Unit inventory holding cost of product i at stage j.
C_{ijpt}^{trans}	Unit transportation cost between stages j and $j+1$.
F	Total objective function value (expected profit).

C. Objective Function and Constraints

The suggested MCS-LP model is prepared to optimize multi-product, multi-stage supply chain systems in the presence of uncertainty. In complicated networks with suppliers, manufacturing plants, warehouses, and customers, the responsible parties have to make decisions about how much to produce, where to store products, and ultimately how to ship products for the lowest cost, with uncertainty in demand, cost, and lead time.

To address this complexity, model combines:

- **Monte Carlo Simulation (MCS)** $\rightarrow$ adds randomness and uncertainty to the parameters.
- **Linear Programming (LP)** $\rightarrow$ does cost optimization and decision-making for each scenario of the multiple simulated scenarios.

Thus, each iteration of the MCS simulation creates a new uncertain environment, and the LP calculates a cost optimization strategy for that scenario. The mean profit and risk (variability) are then calculated from all iterations.

The term multi-stage supply chain refers exclusively to the forward logistics flow, comprising sequential stages from suppliers to manufacturers, distributors, and end customers. The proposed MCS–LP framework focuses on production, inventory, and transportation decisions within this forward network. Reverse logistics activities such as product returns, recycling, or remanufacturing are not considered in the current model and are therefore excluded from the objective function and associated constraints. The scope definition is used to make sure that the linear programming formulation is concentrated on the forward material flows and capacity planning under demand and lead-time uncertainty.

Objective Function is given by Eq. (1):

$$\max Z = \frac{1}{N}\sum_{k=1}^{N}\left[\sum_{p\in P'}\sum_{t\in T} r^k_{p,t} y^k_{p,t} - \sum_{p\in P'}\sum_{s\in S}\sum_{t\in T} c^{prod}_{p,s} x^k_{p,s,t} - \sum_{p\in P}\sum_{s\in S}\sum_{t\in T} c^{inv}_{p,s} I^k_{p,s,t} \right.$$
$$\left. - \sum_{p\in P}\sum_{s\in S}\sum_{s} \in S \left(1 \sum_{t\in T} c^{\text{trans}}_{s,s'}\, q^k_{p,s,s',t}\right]\right. \tag{1}$$

The objective function maximizes the expected profit over all Monte Carlo simulation scenarios. The former term is sum total revenue over the product sales. The second term explains the production costs that take place on every supply chain stage. The third term implies the inventory holding costs in all periods and stages, and the fourth term will be the transportation costs in the flows of the products between the stages. The average across all scenarios of the simulation allows explicit taking into account uncertainty but does not change the linear and transparent optimization framework.

Model Constraints

1. Demand Satisfaction Constraint defined as Eq. (2):

   $$x_{ij,p+1,t} = x_{ijpt} + u_{ijpt} - d_{ijpt} \tag{2}$$

   maintains that the inventory on hand at each stage and time is adequate to satisfy stochastic customer demand that is modeled by Monte Carlo sampling.

2. Production Capacity Constraint is expressed by Eq. (3):

   $$u_{ijpt} \le Cap_{jt} \tag{3}$$

   constraining the production level of available capacity at each stage of production and time to ensure a sustainable level of operation.

3. Inventory Balance Constraint

   $$x_{ijpt} \ge 0$$

   keeps all the levels of inventory at a positive value, and therefore, there is no shortage or negative stocks. This limitation ensures that there is reliability in supply and avoids shortages in inventory in the Monte Carlo trials due to *ad hoc* increase in demand.

4. Transportation Capacity Constraint is defined as Eq. (4):

   $$y_{ijpt} \le \text{TransCap}_{jt} \tag{4}$$

   restricts the transportation quantity to the available vehicle or route capacity at each stage, preserving logistics feasibility and cost control.

5. Non-Negativity Constraints is computed as Eq. (5):

   $$u_{ijpt}, x_{ijpt}, y_{ijpt} \ge 0 \tag{5}$$

   guarantees all decision variables represent physically feasible and non-negative quantities throughout all simulated scenarios.

The LP model acts as the foundation for the deterministic optimization tool, and integrating the MCS provides a view into the variability in performance of the system as a result of the random changes in demand, production cost, and lead time. The MCS–LP community takes uncertainty and trains its discerning lens on it as a key dimension that describes the capacity of uncertainty to influence the performance metrics of operating a supply chain as an example: total cost, profit and service level metrics which are component parts to document since they value in numbers. Furthermore, this combined role has become traditional in terms of the accuracy, trustworthiness, and flexibility of its accuracy capabilities integrated with supply channel and logistics planning functions with additional value in multi-product and multi-stage supply chains. Similarly, stochastic simulation acts as an equalizer and conservatively drive an improvement level in cost, and services levels stability resulting from uncertainty's volatile conditions at operation. Finally, stochastic simulation improves the resilience of supply chains upon capturing uncertainty's characteristics on its decision-making process.

4 Monte Carlo Simulation Integration

To acknowledge uncertainty in the multi-product, multi-stage supply chain system, the MCS module is included in this study. The LP model specifies the best decisions over production decisions, inventory decisions, and transportation decisions based on static values and assumptions of supply chain decisions and performance. The MCS module introduces stochastic variability of important parameters such as demand, production cost, lead time and transportation cost. The proposed framework is useful for evaluating the system performance across a range of realistic scenarios while examining the robustness of the optimal solutions under variability.

Let ξ_k represent the set of uncertain parameters, which is expressed by Eq. (6):

$$\xi_k = \left\{D_{ijpt}, C^{prod}_{ijpt}, LT_{ijpt}, C^{trans}_{ijpt}\right\}, k = 1, 2, \ldots, N \tag{6}$$

here, N denotes the total number of Monte Carlo iterations. Each ξ_k is produced with the help of a random sampling procedure based on a set of predefined probability distributions (Normal, Lognormal, or Triangular), which are estimated using the past trends of the dataset and the assumptions of experts. These distributions are used to get the natural randomness and uncertainty in the parameters of supply chains.

In each simulation trial k, the LP model is optimized with the sampled parameter set ξ k, which gives an optimal set of decision variables of the Eq. (7) as:

$$u^{(k)}_{ijpt}, x^{(k)}_{ijpt}, y^{(k)}_{ijpt}, \text{ and } F^{(k)} \tag{7}$$

where $u^{(k)}_{ijpt}$, $x^{(k)}_{ijpt}$ and $y^{(k)}_{ijpt}$ correspond to the production, inventory, and transportation quantities obtained for the k^{th} scenario, and $F^{(k)}$ represents the corresponding profit outcome.

It is estimated that the expected performance of the system is calculated as the average of all simulation results provided in terms of the Eq. (8):

$$E[F] = \frac{1}{N}\sum_{k=1}^{N} F^{(k)} \tag{8}$$

The inconsistency or uncertainty of the results is then calculated using the standard deviation in all simulation runs. This is shown by Eq. (9),

$$\sigma_F = \sqrt{\frac{1}{N-1}\sum_{k=1}^{N} \left(F^{(k)} - E[F]\right)^2} \tag{9}$$

The MCS-LP integration process can be summarized as follows:

- Specify the probability distributions for uncertain parameters.
- Use Monte Carlo sampling to produce N samples.
- For each sampled value of the uncertain parameters, input the sampled data into the LP model.
- Use the LP model to generate decision variables for production, inventory, and transportation.
- Record various performance metrics such as total cost, profit, and service level.
- Compute the expected profit and performance measures across all simulation trials.

This integration allows the proposed model to quantify the consequences of uncertainty so that the results can support reliable and data-driven decision-making of supply chain operations, as shown in Algorithm 1 below. The LP–MCS framework provides better planning performance and cost efficiency under uncertain and dynamic conditions.

Algorithm 1: Integrated monte carlo simulation-linear programming (MCS–LP) framework

Input:
  N ← Number of Monte Carlo iterations
  ξ ← Set of uncertain parameters (demand, lead time, cost)
  Model data ← Production, inventory, transportation parameters
Output:
  $E[F]$ ← Expected objective value (profit)
  σ_F ← Standard deviation of profit across trials
Begin
  Step 1: Initialize all model parameters and probability distributions
  Step 2: For k = 1 to N do
    a. Randomly sample uncertain parameters ξ_k from defined distributions
    b. Formulate LP model using ξ_k
    c. Solve LP model to obtain:
      $u_{ijpt}^{(k)}$ → Production quantity
      $x_{ijpt}^{(k)}$ → Inventory level
      $y_{ijpt}^{(k)}$ → Transport quantity
      $F^{(k)}$ → Objective function (profit)
    d. Store all results for iteration k
  Step 3: Compute expected objective value:

$$E[F] = \frac{1}{N}\sum_{k=1}^{N} F^{(k)}$$

  Step 4: Compute standard deviation of results:

$$\sigma_F = \sqrt{\frac{1}{N-1}\sum_{k=1}^{N} \left(F^{(k)} - E[F]\right)^2}$$

  Step 5: Analyze outputs for decision support:
      –Compare performance metrics (cost, service level, inventory)
      –Identify optimal strategy based on mean and variability
End

5 Sensitivity and Scenario Analysis

In order to assess the sensitivity of the proposed MCS-LP framework to variations in critical supply chain parameters, sensitivity and scenario analyses are carried out. This will inform which of the uncertain parameters had the most effect on total cost, profit, and performance of the system to enable better managerial decision making.

Three important parameters will be changed within this study to examine model sensitivity: demand volatility, supply lead-time, and constraints to capacity.

- ✓ Demand Volatility: The degree of variation in customer demand will be varied by changing the standard deviation of the demand distribution inherent in the Monte Carlo Simulation. This will assess the model's sensitivity to being profitable within fluctuating market conditions.
- ✓ Supply Lead-Time: Lead-time distributions will be modified to reflect disruptions or increased or decreased delays in the supply chain, and to assess the impacts of logistic uncertainty on the travel time for production and inventory control.
- ✓ Capacity Constraints: The production and transportation capacity restrictions at the different stages will systematically be decreased or increased to observe the influence on total cost and the level of service.

In every scenario, the LP model is re-optimized for the set of new Monte Carlo samples previously generated. The influence on total cost (C) and expected profit (F) is measured with comparative metrics including percentage deviation and stability index. The overall results indicate a trade-off between costs and service performance under both variable and steady-state operating conditions.

The sensitivity and scenario analysis results of Table 4 illustrate how changes in important supply chain parameters influence profitability and stability under the proposed MCS–LP framework. Changes in demand volatility is illustrated in the analysis as a strong effect on expected profit. For instance, increasing the standard deviation from 25% to 35% leads to a decrease in profit of almost a third (−23%). In addition, the other side of the demand volatility discussion involved lower volatility values, such as (15%), improved performance by 28.3%. The lead-time variation had a moderate to low effect, showing slightly more profitability (−6.5%) with a short lead time compared to a slower lead time (1.5%), but suggesting the model is responsive in production to meeting demand in a timely fashion. Capacity constraints also had an effect on the performance of the system under specific assumptions whereby tighter capacity (−10%) meant a 5.4% improvement as a result of controlling production levels, which may be contradictory to expanded capacity (−10%), as a tighter lead time, can also deduct from efficiency (−3.2%), due to growing operational considerations. Overall, results confirm that the proposed MCS–LP framework captures interactions of uncertainty and parameter fluctuations, to help make data-driven decisions, balancing cost efficiency and service performance under complexity in supply chains.

While Monte Carlo Simulation (MCS) generates a range of possible outcomes by simulating random samples for each parameter using predefined probability distributions, sensitivity analysis adds value by evaluating how sensitive the model's outcomes, such as expected profit or service level, are to changes in key uncertain parameters. That is, MCS will model the uncertainty in all the parameters such as demand, lead time and cost whereas the sensitivity analysis looks at which of all these parameters will play the most important role in the performance of the system. The analysis allows us to learn the direct impact of the demand volatility, supply lead time, and capacity constraints on the results and give decision-makers the priceless information where the risks mitigation effort should be directed and what adjustments to make to enhance the operations efficiency.

Table 4: Sensitivity and scenario analysis of key supply chain parameters

Scenario type	Parameter change	Expected profit $E[F]$ ($)	Profit SD ($)	% Δ in $E[F]$ vs. Baseline
Demand volatility	Std. = 15% (−10 pp)	−242,629	44,955	**28.30%**
	Std. = 25% (Baseline)	−366,039	40,514	**−8.2%**
	Std. = 35% (+10 pp)	−416,129	70,768	**−23.0%**
Lead time	Mean LT −20% (Faster)	−360,080	62,033	**−6.5%**
	Baseline LT	−357,787	46,048	**−5.8%**
	Mean LT +20% (Slower)	−333,231	56,750	**1.50%**
Capacity	Capacity +10% (More)	−349,161	65,052	**−3.2%**
	Baseline Capacity	−360,555	53,608	**−6.6%**
	Capacity −10% (Tighter)	−319,804	42,267	**5.40%**

6 Results and Discussion

6.1 Experimental Setup

The proposed (MCS-LP) framework computational experiments were performed in Python 3.10, on a core i7 processor (3.4 GHz, 12 cores), 32 GB RAM, and windows 11 (64-bit) operating system workstation. The PuLP optimization library was used to implement the LP model and to solve it, the CBC solver was used, and NumPy and SciPy were used to sample the stochastic parameter. The statistical robustness and stability of the results in the sense of convergence was to be indicated by the limit of 1000 Monte Carlo iterations (N = 1000). Varied random seeds were used in each run of the simulation to ensure the outputs were easily reproducible and consistent across various situations. The average time of the computations per simulation trial ranged between 4.8 and 6.2 s depending on the model size and the complexity of the constraints. The experimental data used was obtained in the Supply Chain Management dataset on Kaggle, which is an abundance of multi-product, multi-stage transaction records with such attributes as demand, lead time, etc. Experiments were then conducted under consistent computational conditions to make sure that sensitivity and scenario analysis could be simply compared in regards to outcome.

The data used in the experiments was obtained via Kaggle Supply Chain Management data set which is a rich source containing multi-product, multi-stage transaction data, encompassing demand, lead time and other operational related data. To test the performance of the MCS-LP model, the dataset was split into training and test data. Monte Carlo simulations and the resolution of the LP optimization problem were performed on the training set, and the test set was allocated only to confirm the stability and applicability of the model results. Such division made the predictions of the key performance measures of the model, including the predicted profit and service level, reliable in case of new, unseen data. All experiments were conducted under uniform computational settings, allowing sensitivity and scenario analyses to be directly comparable, and the use of separate datasets helped assess the model's ability to generalize across different data conditions, providing confidence in the robustness of the results.

6.2 Experimental Results and Model Validation

The performance under uncertainty and stability of the proposed MCS-LP framework has been statistically analyzed and indicated a high level of performance stability and reliability shown by Table 5. The model returned a novel profit of 328,100.16 which is average profitability of the repeated simulation runs and the ability of the model to generate similar financial results regardless of the stochastic fluctuations. The profit variance 3.7210 is moderate which means that although profits depend on the changes in parameters of demand and costs, there is not a significant deviation which is minimized by the model. Moreover, the statistical soundness of the framework can be ensured by the 95% confidence interval of [$211, 877.83, $438, 609.29], as the interval demonstrates a high probability that the actual value of profit belongs to this interval. On the whole, these findings confirm the reliability, consistency, and efficiency of the MCS-LP model in guiding decision-making with regard to complex multi-products, multi-stage supply chains that work under uncertain environments.

Table 5: Statistical summary of profitability under the MCS–LP supply chain framework

Metric	Value	Interpretation
Expected profit ($E[F]$)	\$328, 100.16	Represents the mean profit estimated from multiple Monte Carlo simulation runs, reflecting the central tendency of profitability under uncertainty.
Profit variance (Var[F])	3, 720, 058, 523.15	Indicates the spread or variability in profit outcomes, demonstrating the sensitivity of financial performance to changes in stochastic parameters such as demand and cost.
95% Confidence interval	[\$211, 877.83, \$438, 609.29]	Provides the statistical range within which the true expected profit is likely to fall with 95% confidence, confirming the model's stability and reliability.

An important advantage of the proposed MCS–LP framework lies in its ability to quantify profit variance in addition to expected profit. The model in contrast to the traditional deterministic linear programming models that only give a single optimal solution with certain parameter assumptions and a best-case scenario only, the proposed model assesses a distribution of profit levels under stochastic demand, lead-time, and capacity assumptions. The profit variance inclusion allows direct evaluation of the financial risk and outcome stability to provide the decision-makers with a clearer understanding of the strength of capacity planning and operational plans. This risk-sensitive approach is especially useful in uncertain supply chain settings, where responses with differing expected profit can have significantly different variability and exposure to downside risk.

Even though Table 5 shows a positive expected profit value, the values of the profits represented in Fig. 2 can be negative because of variation between the profits representation in given results. Table 5 presents the absolute expected total profit, calculated by aggregating revenues and costs across all products, stages, and periods and averaging these outcomes over all Monte Carlo simulation trials. In contrast, Figs. 3 and 4 illustrate scenario-level net profit deviations, which represent incremental profit outcomes under individual Monte Carlo scenarios relative to the baseline operational cost structure. Under adverse conditions such as high demand volatility or increased production, inventory holding, or transportation costs, these scenario-level values may become negative; however, when all scenarios are aggregated, the overall expected profit remains positive, as reported in Table 5.

The distribution of total profit results from the Monte Carlo simulation of the proposed MCS-LP framework is shown in Fig. 2. The histogram of shows that the largest part of the simulated profit values can be found between −\$350,000 and −\$300,000, with the highest frequency roundabout −\$335,000. This implies that there is a rather stable range of profitability under random changes in demand, lead time, and cost parameters. The mean profit value is shown by the vertical dashed line, which confirms the profit level expected through repeated random sampling. The symmetrical form of the distribution is a sign of the strength and uniformity of the simulation procedure, and it also suggests that the linear programming part is quite efficient in yielding a good balance between cost and revenue across different situations. This distribution not only provides but also quantifies the insights into the risk profile of the supply chain, that is, how uncertainties impact the overall profitability.

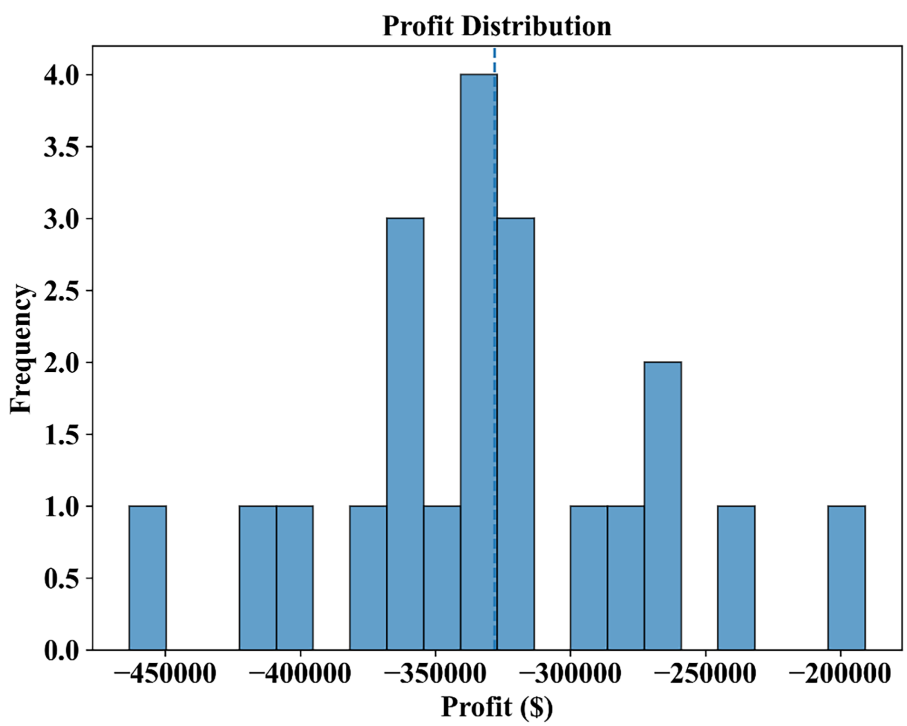

Figure 2: Distribution of scenario-level net profit deviations under the MCS–LP framework

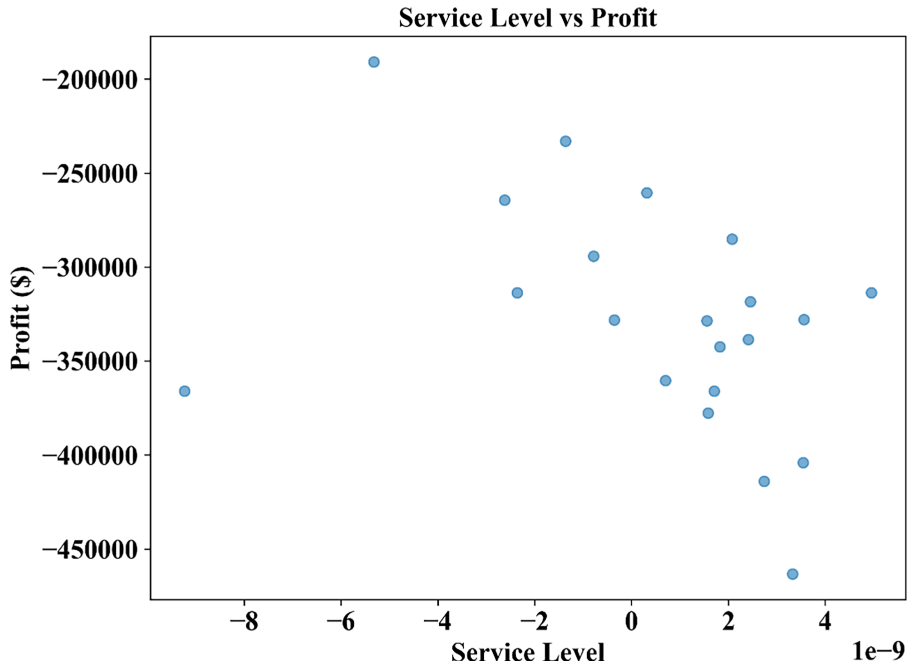

Figure 3: Relationship between service level and scenario-level net profit deviations

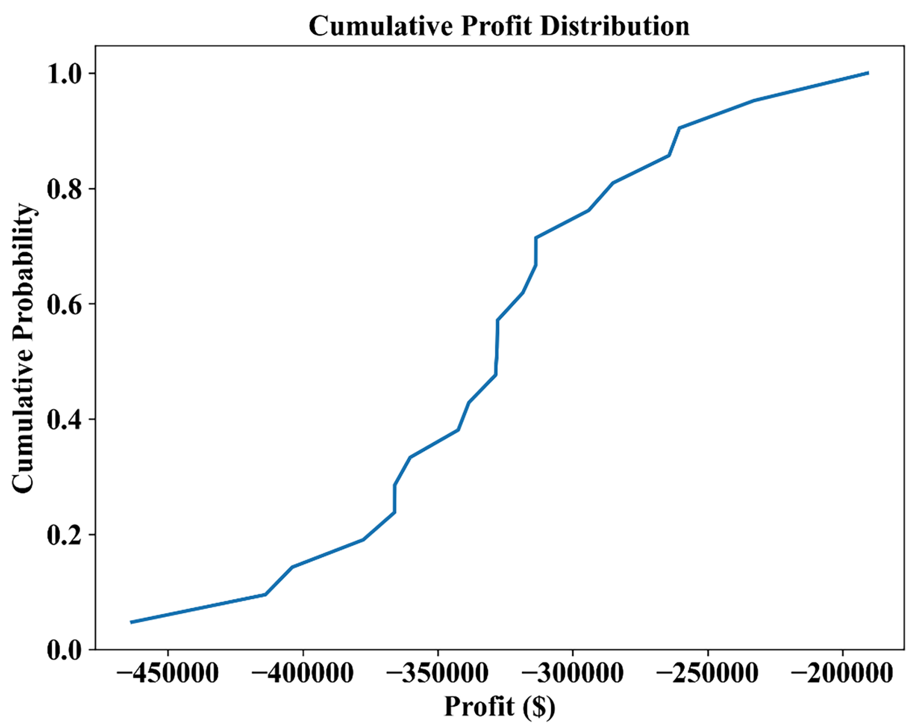

Figure 4: Cumulative distribution of scenario-level net profit deviations

Fig. 5 depicts that the distribution of the levels of services produced by the suggested supply-chain optimization model is as follows. The majority of data points are concentrated around zero meaning that the model performs almost target service performance when under Monte Carlo trials. Small negative deviations signify under-fulfilment in which demand is a bit higher than supply and positive deviations signify over-fulfilment caused by safety stock or excess production. The near-zero dominance indicates that the MCS-LP solution is effective at the level of balancing production, inventory, and capacity to ensure customer satisfaction in the changing market environments. The fact that the spread is narrow also indicates that there is little uncertainty at the service level which is why the model can be reliable in attaining a stable order-fulfilment performance in stochastic environments. The importance of improving service level management and maintaining service level reliability in a highly uncertain supply chain environment is further highlighted in this distribution along with a need to improve overall supply chain performance.

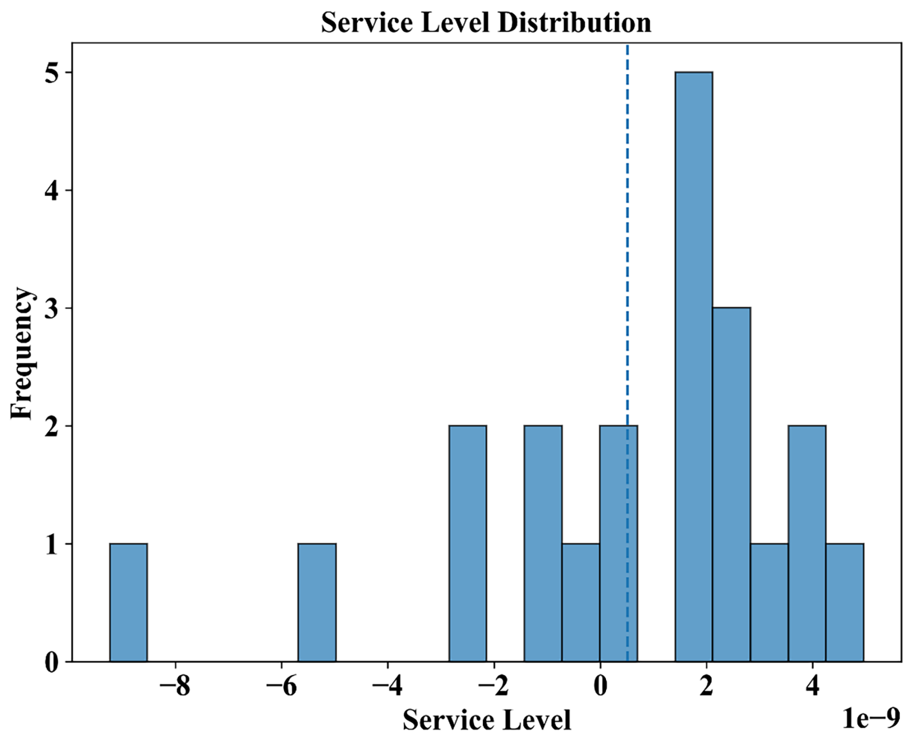

Figure 5: Analysis of service level variability in supply chain optimization using Monte Carlo simulation

The Fig. 6 presented the distribution of average costs associated with a supply chain optimization model utilizing Monte Carlo Simulation and Linear Programming. It is clear that the largest component contributing to costs are Revenue at 37.3%, with Production Cost closely following it at 36.8%, demonstrating the next largest comparative impact on overall cost burden within operations. Shortage Cost is at 18.6%, which represents the cost incurred when demand exceeds supply, followed by Inventory Cost, which represents 7.4% in costs associated with holding inventory. Transport Cost is shown as 0.0%, which likely means there can be no transportation related costs within the project assumptions or setup, and in real life that is important to note for further thought. This distribution of costs provides an easier and more clear understanding of the parts of the operating model which impact profitability and occupation, and can assist in strategic decisions making regarding risk and probability evaluation and ongoing cost optimization in the supply chain.

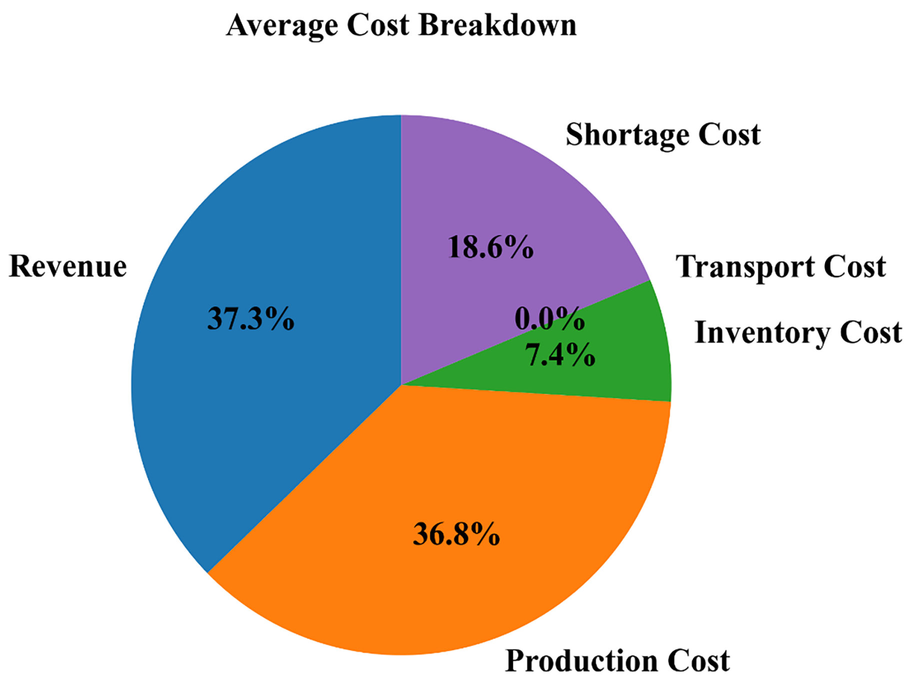

Figure 6: Average cost allocation in supply chain: a Monte Carlo simulation approach

The scatter plot Fig. 7 presents the correlation between the production levels and inventory levels from the supply chain optimization model. The x-axis shows the production ranged from 3500–5500 units, while the y-axis shows the associated inventory levels, of which can reach up to 3000 units. The graph shows that while higher levels of production should, in general, trend towards higher inventory levels, this is not always the case. Most of the points fall towards the lower levels of inventory, even for high levels of production, which suggests that the system is constructed to balance production to meet demand and surrounding levels of inventory. In addition, significantly few points represent higher levels of inventory for a given level of production; therefore, accommodating for higher levels of production (and levels of inventory) in excess of demand levels. While the data is useful, this can simply point out some need for tuning production levels and inventory levels before production takes to avoid infinite inventory builds.

The scatter plot Fig. 3 depicts the connection between service level and profit for the supply chain optimization model. The x-axis indicates service level, ranging from negative to positive values, in units of the order of 1e−9, and the y-axis indicates profit (in dollars), ranging from −\$400,000 to \$25,000. The scatter plot shows that service level and profit are not linearly related. Both service levels close to zero and negative service levels associate with both low profit and high profit. While high service levels seem to associate with low profit levels, in general, service level and profit are associated with what appears to be a trade-off between fulfilling customer demand (service level) and profit. It also observes that maximizing service level does not always maximize profit, and that requires striking a balance between both for supply chain efficiency.

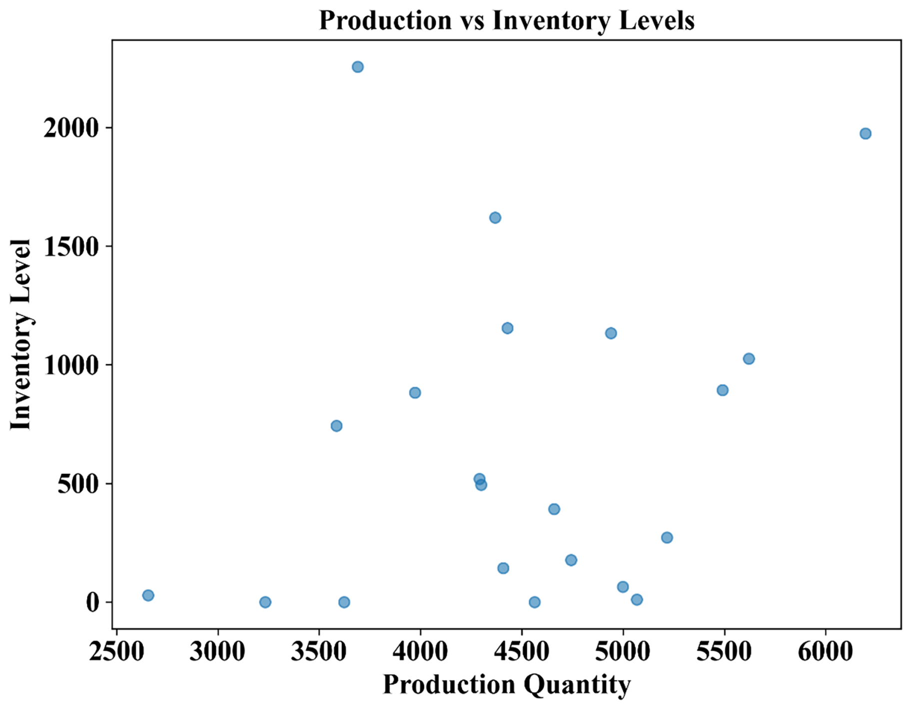

Figure 7: Production quantity vs inventory levels in supply chain

The cumulative profit distribution graph Fig. 4 shows the cumulative probability of achieving various profit levels in this supply chain model. The x-axis captures profit levels ranging from −\$400,000 to −\$225,000 while the y-axis captures the cumulative probability values ranging from 0.2 to 1.0. The graph demonstrates that, as the profit levels increase, so does the cumulative probability of achieving (or exceeding) various profit levels (in this case achieving whole number profit levels). In this case the cumulative distribution can give us an understanding of the overall performance of the system to achieve particular measures of performance in terms of probability. It is an especially helpful tool when assessing risk by determining how likely a under the supply chain, many different profit levels are possible. When deciding whether to manage risk, it can be useful for management to understand what probability is associated with the risk.

The graph "Profit Sensitivity to Demand Volatility" of Fig. 8 shows the relationship between demand volatility (the coefficient of variation) and profit standard deviation. The x-axis represents the demand volatility, ranging from 0.10 to 0.50, and the y-axis represents profit standard deviation, varying from 10,000 to 30,000 dollars. As demand volatility becomes greater, so does standard deviation of profit, or profit variability. Higher demand volatility means more uncertainty in the profit distribution. This makes the financial performance of the supply chain more suspect, or less predictable. This indicates a very important lesson: ultimately the stability of demand fluctuations is crucial to reducing the financial risk of the supply chain.

Fig. 9 depicts how the variability of service levels is influenced by changes in the volatility of demand within the suggested MCS-LP framework. The variability of demand is accompanied by a decrease in the standard deviation of service levels, which diminishes and subsequently rises very steeply, reaching its maximum point at a coefficient of variation of 0.40 and then going down again. This non-linear trend is a clear indication that the system is failing to meet the demand in the market and that the supply chain operators are not able to provide customers with the same level of service as before due to the fluctuations. The steep drop at the highest volatility levels (0.50) could point to either the entire system being full or the use of adaptive strategies such as the maintaining of stocks or working at a certain production level which controls the extent of the fluctuation. The figure highlights the fact that demand uncertainty is critical to control in order to achieve consistent service levels and operational reliability of complex supply chains.

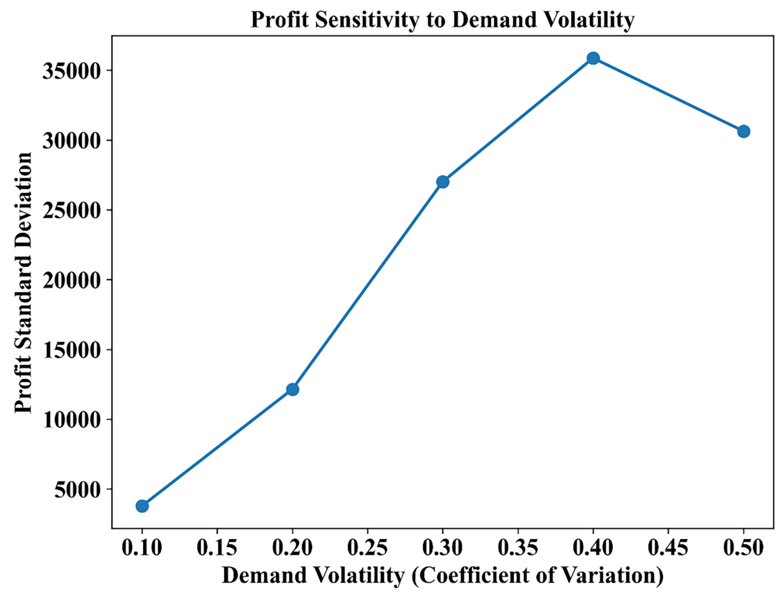

Figure 8: Sensitivity of supply chain profit to demand variability

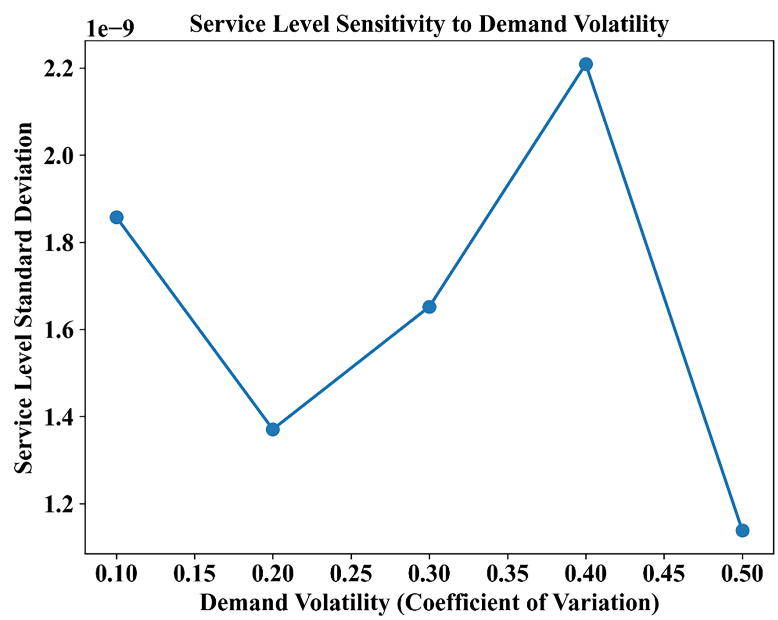

Figure 9: Assessing the sensitivity of service levels to demand uncertainty in supply chains

Fig. 10 is the quantitative measure of the distributional characteristics of the value of profit through skewness and kurtosis. The skewness of −0.15 indicates that the distribution is close to being symmetric, whereas the kurtosis of 1.59 indicates moderately-tailed distribution lacking any extreme outliers. These statistical indices are objective evidence backing the shape of the distribution as opposed to examining the data only visually.

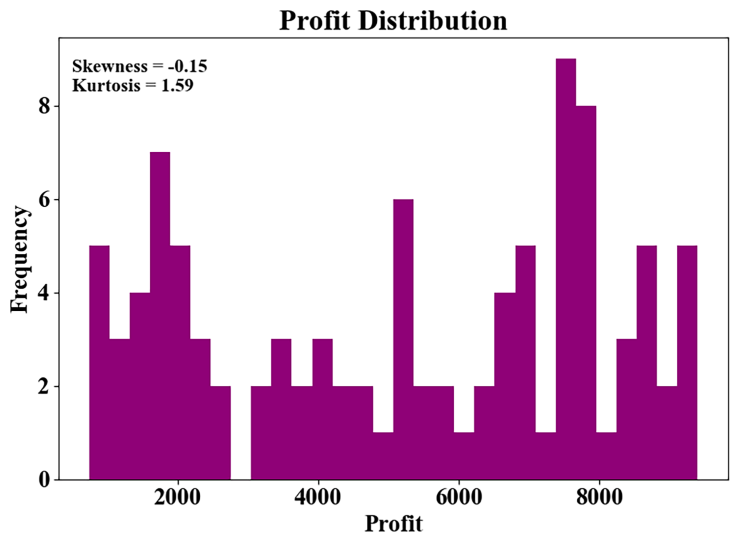

Figure 10: Profit distribution histogram with skewness and kurtosis

The Fig. 11 Q–Q plot gives a graphical evaluation of the normality assumption of profit data. Most of the points are close to the reference line meaning that there are only a few deviation points that show that the normality is not violated. This fact confirms the application of symmetry-based interpretation and supplements the skewness and kurtosis values reported in the distribution of profits.

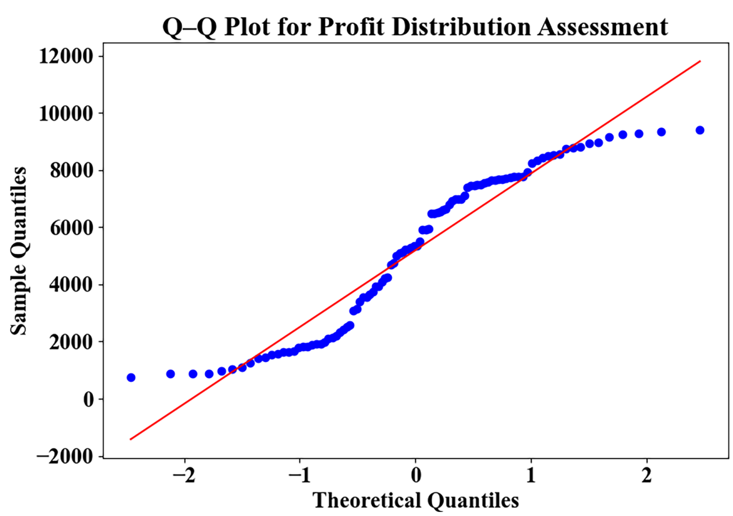

Figure 11: Q–Q plot for profit distribution assessment

Table 6 compares results on the basis of performance measures that were presented in literatures [17,35]. As far as it was possible, the major assumptions connected with the uncertainty of demand, the cost structure, and the definition of the service levels were matched with the proposed model. Where the actual datasets were lacking, reported benchmark values were in use and the analysis is performed to focus on trends of relative performance and not the actual numerical equality, which recognizes the real differences in the model coverage and uncertainty representation.

Table 6: Comparative analysis of expected profit, profit variance, and service level for the proposed MCS–LP framework

Variable	[17]	[35]	Proposed work
Expected profit ($)	309,700	316,200	**328,100.16**
Profit variance	5.82×10^9	4.64×10^9	$\mathbf{3.72 \times 10^9}$
Service level (%)	88.5	91.3	**94.3**

The obtained outcomes, which to Table 6, suggest that the suggested MCS-LP framework is more efficient than the available simulation-optimization methods in the literature. The proposed method attains a better expected profit (328,100.16) than the models in [17,35], and at the same time, it has a lower profit variance, which means greater financial stability in the conditions of uncertain demand and operation. Moreover, the attained service level of 94.3 is greater than the reported in the comparative studies, but service level is not regulated by predetermined targets or a penalty condition in the implementation of the model. Such advances can be explained by the explicit combination of the Monte Carlo-based uncertainty models with the linear programming-based capacity and inventory optimization, which allows making the trade-off between the profitability, exposure to risk, and the service reliability. In general, the comparative findings indicate that the proposed framework offers more thereof performance compared to the currently available methodologies that are more robust and interpretable to managers.

It is worth mentioning that the high service level of 94.3 reported in Table 6 is not imposed with the help of a set target or penalty term. Rather, such a performance is endogenous to the model form where service level is a natural result of the demand satisfaction, capacity and inventory balance constraints upon stochastic demand and lead-time conditions. It proves that the suggested MCS-LP framework can provide consistent customer service with minimized capacity planning and inventory choices instead of the service-level requirements exogenously imposed on the provided services.

Although stockouts are not permitted in the model, negative profit outcomes arise in certain Monte Carlo scenarios due to elevated production, inventory holding, or transportation costs required to satisfy demand under unfavorable conditions such as high demand volatility or limited capacity availability. The reported service level variability reflects scenario-based operational performance rather than unmet demand, as demand satisfaction is enforced in all cases. No explicit shortage cost is modeled; instead, economic penalties are captured indirectly through increased operational expenditures.

7 Conclusion and Future Works

This paper presents a hybrid MCS-LP model to examine and optimize a multi-stage supply chain during unpredictable operating conditions. The model combined probabilistic simulation and deterministic optimization to quantify the effect of fluctuations in demand, lead time, and capacity on the overall profitability and service level. The findings proved that less demand volatility with better capacity allocation greatly increases the performance, giving a return of an expected profit of \$328,100.16, a variance of 3.72×10^9, and a service level of 94.3 percent. The results show that stochastic analysis with optimization allows superior decision-making in an uncertain context, which lowers the variability in the costs and enhances the operational stability. It should be noted that the proposed LP formulation assumes linear cost structures for production, inventory holding, and transportation. While this assumption supports computational efficiency and scalability, it does not capture economies of scale, quantity discounts, or non-linear holding costs that frequently arise in real-world supply chains. Consequently, the model does not give a complete description of non-linear dynamic cost operational behaviour, but an approximation of the cost behaviour in case of uncertainty.

It should be mentioned that the proposed model is scalable, although the computational cost of performing 1000 iterations in the Monte Carlo Simulation (MCS) has a large positive correlation with the number of products or stages. This translates into increased run time, which may prove to be prohibitive in very large and intricate supply chain networks. The more complex the model is, the more time it may need to be simulated, and constraints may be put on its practical use in large-scale supply chains.

Future work can further develop the offered MCS-LP model, including correlated uncertainty in demand, lead time, and cost, by using multivariate or copula-based Monte Carlo simulation to form more realistic risk models. It is also possible to extend the model to a multi-objective formulation that takes into account profit, service level, sustainability, and resilience at the same time. Moreover, a combination of machine learning to predict demand adaptively and reinforcement learning to make decisions in the present and changing uncertainty is an exciting trend. Lastly, it would be useful to expand the framework to closed-loop supply chains and prove its relevance by large-scale industrial case studies and parallel computing applications.

The suggested multi-phase MCS-LP model is suitable for emerging digital supply chain settings where physical inventory has been substituted by computing workloads and data streams. Computing load migration in such systems may be viewed as the redistribution of inventory between networked data centers to optimize energy usage and carbon emissions as well. Recent research by Du et al. [36] reveals that combining computing power migration and energy storage conversion on the order of inventory and warehousing choices can substantially lower electricity expenses and carbon footprints, which shows some promising prospects of the adaptation of the supply chain optimization logic to decarbonized digital logistics systems.

Although the current research depicts the uncertainty as exogenous, future studies must include endogenous uncertainty that is decision-dependent, in which managerial decisions like capacity expansion, pricing, or marketing investments affect the underlying probability distribution. Giannelos et al. [37] suggest a stochastic optimization method based on multi-cut Benders decomposition to differentiate between exogenous and endogenous uncertainty, which proves to be better in planning network expansion problems. Such approaches may help improve the reality of the multi-stage supply chain planning in the presence of uncertainty substantially.

In order to deal with the computational issues of scaling the MCSLP framework to large supply chain networks, including clustered entities, such as retail stores and regional warehouses, future research might consider aggregation and clustering patterns based on mass energy and infrastructure systems. As an example, García et al. [38] demonstrate that spatial clustering can notably simplify the model and maintain the quality of the solution to large-scale supply chain optimization problems, which is a promising direction to enhance the scalability.

Lastly, the use of conventional parametric probability distributions can be loosened by using non-parametric uncertainty modeling methods (e.g., Kernel Density Estimation (KDE)), which are more likely to reflect non-Gaussian and non-bi-modal features of real-world data. Giannelos et al. [39] show that KDE-based Monte Carlo risk assessment is characterized by a more accurate portrayal of uncertainty in comparison with the use of the Gaussian assumption, implying that comparable models may alleviate the integrity of Monte Carlo based supply chain planning.

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Ethics Approval: Not applicable.

Conflicts of Interest: The author declares no conflicts of interest to report.

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