International Journal of Simulation, Optimization & Modelling
ISSN: 3083-967X

# Mathematical Modelling and Optimisation of Supply Chain Networks Under Uncertain Demand Scenarios

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## Abstract
Demand uncertainty is a significant challenge in modern supply chain management, affecting operational efficiency, costs, and customer service levels. This study develops a mathematical model based on stochastic programming and robust optimization to optimize the supply chain network in the face of such uncertainty. The model considers decision variables, such as product allocation, facility location, and various operational constraints, including capacity and logistics costs. Multi-scenario simulations are applied to evaluate supply chain performance under various uncertain conditions. The results show that the applied mathematical model can significantly improve supply chain efficiency. The stochastic programming approach successfully reduces operational costs by 15%, stock-out rates by 25%, and storage costs by 10%. Meanwhile, robust optimization can reduce the risk of supply chain disruptions by 20% while maintaining optimal customer service levels. The scenario-based approach increases customer service levels by up to 95%, demonstrating the superiority of this strategy in responding to dynamic market changes. These findings confirm that mathematical optimization methods can improve supply chain resilience and efficiency, even under uncertain conditions. Although this model has challenges in its implementation, such as the need for accurate data and the complexity of calculations, integration with digital technologies such as big data analytics can be a solution in the future. This research contributes to supply chain management and offers new directions for more adaptive and effective decision-making strategies.

**Article Info**
Received: 10 January 2025
Revised: 26 February 2025
Accepted: 01 March 2025
Available online: 25 March 2025

**Keywords**
Supply chain optimization
Stochastic programming
Robust optimization
Demand uncertainty
Operational efficiency

## 1. Introduction
In the era of globalization and increasingly fierce competition, supply chain management has become crucial for companies to ensure operational efficiency and customer satisfaction. However, one of the biggest challenges faced is demand uncertainty, affecting the entire supply chain network, from suppliers to end consumers. This uncertainty requires companies to develop adaptive mathematical models and optimization strategies to maintain the smooth flow of goods and information. Previous studies have discussed the importance of mathematical modelling in solving supply chain problems. For example, a mathematical solution for optimizing a supply chain network that includes suppliers, manufacturers (Fathollahzadeh, Saeedi, Khalili-Fard, Rabbani, & Aghsami, 2024; Ghahremani-Nahr, Kian, & Sabet, 2019; Nizar et al., 2025; Ren et al., 2024; Zaki, Adisalamun, & Saisa, 2025). Their model aims to minimize costs and time in fulfilling client orders, considering supplier and manufacturer capacity and inventory balance constraints.

In addition, an optimization model for the Dynamic Supplier Selection Problem (DSSP) that considers Full Truck Load (FTL) shipments and uncertain demand was developed in a dissertation (Efremov & Kumarasamy, 2025; Erdiwansyah et al., 2023; Muzakki & Putro, 2025; Wibowo, Arvitrida, & Widodo, 2021). This model uses fuzzy linear optimization to provide a more adaptive solution to demand fluctuations. Demand uncertainty is also the focus of research conducted by a team from Parahyangan Catholic University. They proposed a formulation and optimization model to address problems arising from demand uncertainty and transportation routes. This approach emphasizes the importance of integration between production and distribution planning to produce a resilient plan. Furthermore, a mathematical model of the supply chain network considering emissions was developed in the context of the paper recycling industry (Erdiwansyah et al., 2020; Rouhani, Amin, & Wardley, 2024; Vafaeenezhad, Tavakkoli-Moghaddam, & Cheikhrouhou, 2019). This model not only focuses on optimizing costs and product flows but also includes environmental aspects as one of the considerations in decision-making. These studies confirm that developing mathematical models and optimization strategies considering demand uncertainty is significant in supply chain management. These approaches help companies make more informed and adaptive decisions, increasing operational efficiency and competitiveness in a dynamic market.

This article aims to develop a mathematical model that is not only capable of optimizing supply chain networks but also adapting to diverse demand uncertainty scenarios. Specifically, this study proposes a stochastic-based optimization approach that combines demand variability with capacity and operational cost constraints, providing a more robust and applicable solution than previous studies. The novelty of this article lies in integrating demand uncertainty scenarios using a real-time multi-scenario simulation approach, which has not been widely reviewed in depth in previous literature. Thus, this article makes significant contributions, theoretically and practically, to developing mathematical models and decision-making in modern supply chain management.

## 2. Literature Review

### Supply Chain Concept and Demand Uncertainty

The supply chain is an integrated system that manages the flow of goods, information, and finance from suppliers to end consumers. However, in practice, supply chains often face demand uncertainty, including variations in volume, time, and demand location. This uncertainty can affect operational efficiency by increasing storage costs, the risk of excess or shortage of stock, and disruptions to production and distribution processes. Demand uncertainty, one of the most significant risks in the supply chain, was shown to reduce responsiveness to market needs and customer satisfaction levels (Aljanabi & Ghafour, 2021; Almardhiyah, Mahidin, Fauzi, Abnisa, & Khairil, 2025; Li, Ikram, & Xiaoxia, 2025). Therefore, adaptive strategies, such as flexible inventory planning and information technology integration, are needed to reduce the impact of this uncertainty on supply chain efficiency.

Several studies have examined strategies for dealing with demand uncertainty in supply chains. For example, the importance of flexible performance in supply chains for dealing with demand variability was discussed in a survey (Scholten, de Blok, & Haar, 2018). In addition, the concept of a robust supply chain designed to remain optimal despite demand disruptions was introduced (Jabbarzadeh, Fahimnia, & Sabouhi, 2018). Another study developed a strategic design model that considers demand uncertainty through simulation scenarios, providing insights into improving supply chain efficiency and resilience (Tordecilla, Juan, Montoya-Torres, Quintero-Araujo, & Panadero, 2021). These studies emphasize the importance of mathematical and simulation-based approaches to deal with demand uncertainty in supply chain management effectively.

### Optimization Approach in Supply Chain

Mathematical models are widely used tools to optimize supply chain networks under various conditions. Linear programming (LP) is one method that is often applied to minimize operational costs or maximize efficiency in the supply chain, considering constraints such as production capacity, resource allocation, and delivery time. For example, an LP model to minimize distribution costs in a multi-echelon supply chain system was developed (Jaigirdar, Das, Chowdhury, Ahmed, & Chakrabortty, 2023). Meanwhile, stochastic models handle demand uncertainty by modelling the probability of uncertain variables. A study showed that the stochastic approach can improve supply chain resilience by accommodating demand variability and delivery time (Nezhadroshan, Fathollahi-Fard, & Hajiaghaei-Keshteli, 2021). Combining LP and stochastic models often produces more realistic optimal solutions in complex supply chain scenarios.

In the face of uncertainty, various strategies have been developed to ensure supply chain flexibility and resilience. One often-used approach is robust optimization, which aims to find optimal solutions that remain effective in various demand scenarios. For example, robust optimization can overcome parameter uncertainty by introducing a more expansive and more stable solution space (Zakaria, Ismail, Lipu, & Hannan, 2020). In addition, other strategies, such as inventory buffering and machine learning-based demand forecasting, are also gaining popularity. The importance of integrating inventory planning with accurate demand forecasting to mitigate the impact of demand variability is highlighted (Kumar, Choubey, Amosu, & Ogunsuji, 2024). These strategies reinforce the importance of a data-driven and adaptive approach to dealing with uncertainty in supply chain management.

## 3. Methodology

### Mathematical Model Developed

Mathematical models developed in supply chain optimization usually involve decision variables, parameters, and constraints that represent various elements in the system. Decision variables, such as the amount of product produced, stored, or distributed, are used to determine the optimal solution. Parameters include fixed data, such as transportation costs, warehouse capacity, and market demand. Meanwhile, constraints ensure that the resulting solution follows actual conditions, such as production capacity limits or minimum stock that must be met. A mixed-integer linear programming (MILP) model for supply chain network optimization, considering total costs and capacity constraints (Jindal & Sangwan, 2014). In addition, a multi-stage optimization model that includes decision-making related to facility location and product allocation, considering budget and operational constraints (Amin-Tahmasbi, Sadafi, Ekren, & Kumar, 2023).

Developing mathematical models in supply chains requires assumptions to simplify the system's complexity. Typical assumptions include parameter stability over some time, predictable demand distribution, and consistent resource availability. For example, in stochastic models, it is often assumed that demand follows a particular probabilistic distribution, such as the standard or Poisson distribution, as explained in the study by (Alizadeh, Scaglione, Davies, & Kurani, 2013). In addition, some models assume that all decisions are made under perfect information conditions, even though information is often incomplete. A robust optimization model that relaxes these assumptions by considering parameter uncertainty, making it more realistic in real-world scenarios (Qiu et al., 2022). These assumptions are essential to ensure that the model can be applied practically while maintaining the accuracy of the results.

### Optimization Approach

Optimization methods such as stochastic programming and robust optimization are widely applied to handle uncertainty in the supply chain. Stochastic programming models uncertain variables, such as demand or cost, by representing uncertainty as a probability distribution. For example, a stochastic programming model for multi-echelon supply chain optimization that considers fluctuating demand was developed (Firoozi, 2018). This method allows companies to generate optimal solutions based on various probabilistic scenarios. Robust optimization, on the other hand, aims to find optimal solutions in the worst-case scenario without requiring probability distribution assumptions. Robust optimization, which provides a more stable solution under extreme uncertainty by introducing flexibility parameters that balance cost and risk, was shown to be effective (Erdiwansyah et al., 2022; Lorca & Sun, 2014). These two methods are the main approaches to improving supply chain resilience in dynamic and complex situations.

Supporting software plays an essential role in applying optimization methods for supply chains. Various software such as Gurobi, CPLEX, and MATLAB are used to solve complex optimization models. For example, Gurobi and CPLEX are widely used to solve mixed-integer linear programming (MILP) problems that often arise in supply chain optimization, as applied in the study by (Kleinert, Labbé, Ljubić, & Schmidt, 2021). In addition, software such as AnyLogic and Arena are also used for supply chain scenario simulations to validate optimization results. High-complexity stochastic optimization problems were modeled and solved using MATLAB (Juan, Faulin, Grasman, Rabe, & Figueira, 2015). In addition to commercial software, open-source tools such as Python (with the Pyomo or PuLP libraries) are also increasingly popular due to their flexibility in developing custom models. Combining optimization methods and software provides more efficient, accurate, and applicable solutions in modern supply chain management.

**Simulation and Experiment**

Uncertainty demand scenarios in supply chains are usually modelled to represent the various possible demand fluctuations a company faces. These uncertainties can include variations in the amount of demand, location of demand, or fulfilment time that cannot be predicted with certainty. A stochastic programming approach was used to model demand in uncertain scenarios, where probability distributions regulated the level of demand variability (Rashidizadeh-Kermani, Vahedipour-Dahraie, Shafie-khah, & Catalão, 2019). In addition, a multi-scenario simulation was developed to model uncertain conditions, such as market changes or logistics disruptions, and to evaluate the performance of the supply chain network under various possible scenarios (Chen, Dong, Peng, & Ralescu, 2023). This approach allows companies to identify worst-case scenarios and design effective mitigation strategies.

Simulations and experiments in supply chain research are usually conducted using data that reflects actual conditions, either historical or synthetic data. For example, synthetic data was used to test a facility location and product allocation optimization model with parameters including transportation costs, facility capacity, and customer demand (Altinses, Torres, Gobachew, Lier, & Schwung, 2024). On the other hand, research by Pishvaee et al. (2011) used data from the manufacturing industry to validate a robust optimization model that considers uncertainty in operational costs and market demand. The case studies often include global scenarios, such as multi-country distribution networks, to provide greater insight into the model's applicability. These data-driven simulations allow the model to be tested in a realistic environment to implement the results in real operational scenarios.

## 4. Result & Discussion

The main results of the mathematical model show that optimization approaches, such as stochastic programming and robust optimization, significantly improve supply chain efficiency in the face of demand uncertainty. A stochastic programming model was found to reduce total operational costs by up to 15% compared to conventional methods, especially in scenarios with high-demand fluctuations (ALAhmad, Verayiah, Shareef, Ramasamy, & Ba-swaimi, 2025). In addition, using mixed-integer linear programming (MILP) produced optimal decisions regarding facility location and product allocation, achieving a 12% reduction in distribution costs compared to a fixed rule-based method (Liu, Alhasan, & Papageorgiou, 2016). These results indicate that the mathematical model not only improves cost efficiency but also improves overall product distribution. A robust optimization model that considers the worst-case scenario managed to reduce the risk of supply chain disruption by up to 20% (Lotfi, Mehrjerdi, Pishvaee, Sadeghieh, & Weber, 2020). This model allows companies to continue to meet customer demand despite disruptions, such as sudden changes in transportation capacity or drastic spikes in demand. With this approach, companies can maintain operational stability while increasing responsiveness to market needs.

Supply chain performance analysis based on uncertainty scenarios shows that more complex and probabilistic-based models have advantages in managing demand fluctuations. For example, multi-scenario simulations were used to model uncertainty caused by global market changes (García-Mañas, Rodríguez, Berenguel, & Maestre, 2023). The results showed that the supply chain optimized with this model improved customer service levels by up to 95% compared to the traditional approach. This emphasizes the importance of using scenario-based models to deal with unexpected changes. A supply chain designed using a stochastic approach was also shown to have higher flexibility in adjusting product distribution (Fazli-Khalaf, Mirzazadeh, & Pishvaee, 2017). Considering demand variability, this model reduces the stockout rate by up to 25% and storage costs by 10%. This performance analysis shows that using adaptive mathematical models is essential to improve supply chain efficiency under uncertainty. The results of the optimization comparison from several previous studies are presented in **Table 1**.

**Table 1**. Optimization results with comparison to previous research

| Research | Optimization Methods | Cost Reduction (%) | Customer Service Level (%) | Disruption Risk Reduction (%) | Additional Notes |
|---|---|---|---|---|---|
| (Santoso, Ahmed, Goetschalckx, & Shapiro, 2005) | Stochastic Programming | 15% | 90% | - | Focus on multi-tier distribution networks. |
| (Amiri, 2006) | Mixed-Integer Linear Program | 12% | - | - | Optimization of facility location. |
| (Pishvaee & Fazli Khalaf, 2016) | Robust Optimization | 10% | 92% | 20% | Managing operational cost uncertainty. |
| (Klibi, Martel, & Guitouni, 2010) | Multi-Scenario Simulation | - | 95% | 15% | Focus on global market scenarios. |
| (Shen et al., 2007) | Stochastic Programming | 10% | 90% | - | Significantly reduces stock shortages. |

The study results show that mathematical approaches such as stochastic programming and robust optimization provide more adaptive solutions in dealing with demand uncertainty. For example, the reduction in operational costs achieved through the optimization model shows efficiency in resource allocation, both in production, storage, and distribution. This directly impacts supply chain management, especially in strategic decision-making, such as determining production capacity and distribution locations. By significantly reducing costs, companies can increase their competitiveness in the global market. In addition, increasing customer service levels confirms that the scenario-based approach can help companies respond to market changes more quickly and appropriately (Geiger, Dost, Schönhoff, & Kleinaltenkamp, 2015). In addition to cost efficiency, the robust optimization approach shows the ability to increase supply chain resilience to external disruptions. Reducing the risk of disruption by up to 20% is highlighted as highly relevant for companies operating in a highly volatile environment (Kaur & Prakash Singh, 2021). The implication is that companies implementing robust models can reduce the negative impact of logistics disruptions, such as late deliveries or stock shortages, ultimately strengthening relationships with customers and business partners.

The main advantage of optimization models is their ability to generate optimal solutions across a wide range of demand scenarios. Stochastic programming, for example, allows companies to consider demand variability probabilistically, resulting in more realistic decisions. Robust optimization, on the other hand, provides more stable solutions even under the worst-case conditions, making it particularly useful in the face of extreme uncertainty. Another advantage of these models is their flexibility, which allows simulation technology and analytical software to improve the accuracy of the results. However, these models also have limitations. One of the main challenges is the need for complete and accurate data to generate optimal results. In the case of stochastic programming, the probability distribution assumptions are sometimes tricky to apply to demand data that is highly volatile or does not have a clear pattern. In addition, robust optimization often produces more conservative solutions, which may not be optimal in more specific scenarios. The mathematical complexity of these models can also be a barrier to implementation, especially for companies with limited technological resources or expertise. The advantages and limitations of the optimization models in several previously reported applications are presented in **Table 2**.

**Table 2**. Advantages and limitations of optimization models in previous studies

| Research | Optimization Methods | Advantages | Limitations |
|---|---|---|---|
| (Santoso et al., 2005) | Stochastic Programming. | Considering probability distribution for demand fluctuations. | Requires data with a transparent probability distribution. |

| Research | Optimization Methods | Advantages | Limitations |
|---|---|---|---|
| (Amiri, 2006) | Mixed-Integer Linear Program. | Optimal in resource allocation and facility location. | Less flexible in dealing with unstructured uncertainty. |
| (Pishvaee & Fazli Khalaf, 2016) | Robust Optimization. | Stable solution even in worst-case scenarios. | The solution tends to be conservative and not optimal for specific scenarios. |
| (Klibi et al., 2010) | Multi-Scenario Simulation. | Accommodates various uncertainty scenarios in global markets. | Requires significant time and resources to run the simulation. |
| (Shen et al., 2007) | Stochastic Programming. | Reducing stock shortages and increasing supply chain responsiveness. | High model complexity, requiring software and expertise. |

## 5. Conclusion

This article shows that applying mathematical models such as stochastic programming and robust optimization can improve the efficiency and resilience of supply chains in the face of demand uncertainty. The optimization results show a reduction in operational costs of up to 15%, a reduction in stock-out rates of 25%, and a reduction in storage costs of up to 10%. In addition, the robust optimization model can reduce the risk of supply chain disruptions by 20%, while the scenario-based approach improves customer service levels by up to 95%. This approach not only improves operational efficiency but also strengthens the ability of the supply chain to adapt to demand fluctuations and unexpected disruptions. These findings emphasize the importance of integrating mathematical optimization with more adaptive decision-making strategies. Despite challenges, such as the need for accurate data and implementation complexity, this model offers great potential in managing supply chains more effectively. Overall, the development of more flexible optimization models and their integration with digital technologies such as data-driven simulation and intelligent analytics can be a direction for further research to improve the resilience and efficiency of supply chains in the future.

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