STRATEGIC GLOBAL SUPPLY NETWORK PLANNING UNDER DISRUPTIONS

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To my family and friends..

ABSTRACT

The effective management of disruptions in global supply chain networks has become a critical aspect of strategic decision-making, particularly owing to the increasing frequency of worldwide disasters. This study aims to research and identify strategies that supply chain managers can employ to mitigate the impact of disruptions on their supply chains. Specifically, we focus on strategic disruption planning for a global supply chain network, analyzing the consequences of multiple types of disruptions within a finite planning horizon segmented into discrete time periods. To address this, optimal decisions related to procurement, production, distribution, and demand satisfaction are determined using Mixed-Integer Linear Programming (MILP) models. These models are classified in two types: deterministic model, uses expected values, and stochastic model, which allows us to analyze the impact of various disruption scenarios. To ensure the realism of our approach, a performance comparison is conducted by incorporating a simulation approach on the best solutions, considering both deterministic and stochastic models. In addition, hypothesis testing is integrated to the simulation results to compare and identify the most cost-efficient model. This rigorous statistical analysis provides valuable insights into the relative performance of distinct models across diverse disruption scenarios. By providing insights into effective strategies for managing disruptions in global supply chain networks, this thesis makes a valuable contribution to the existing literature on supply chain management.

ÖZETÇE

Küresel tedarik zinciri ağlarında meydana gelen aksaklıkların etkin yönetimi, özellikle dünya çapında yaşanan felaketlerin artan sıklığı nedeniyle stratejik karar verme süreçlerinde kritik bir öneme sahip olmuştur. Çalışmamız, tedarik zinciri yöneticilerinin tedarik zincirlerindeki aksaklıkların etkisini azaltmak için kullanabileceği stratejileri araştırmayı ve belirlemeyi amaçlamaktadır. Özellikle, küresel tedarik zinciri ağı için stratejik aksaklık planlamasına odaklanarak, sonlu bir planlama dönemi içinde birden çok türde aksaklığın sonuçlarını analiz ediyoruz. Bu doğrultuda, tedarik, üretim, dağıtım ve talep karşılama ile ilgili optimal kararlar, Karışık Tamsayılı Lineer Programlama (MILP) modelleri kullanılarak belirlenir. Bu modeller iki tipe ayrılır: deterministik model, beklenen değerleri kullanır ve stokastik model, çeşitli kesinti senaryolarının etkisini analiz etmemizi sağlar. Yaklaşımımızın gerçekçiliğini sağlamak için, en iyi çözümlerde belirlenen belirlemeli ve stokastik modelleri içeren bir simülasyon yaklaşımı ile performans karşılaştırması yapılır. Ayrıca, hipotez testi, en maliyet-etkin modeli karşılaştırmak ve belirlemek için simülasyon sonuçlarına entegre edilir. Bu sıkı istatistiksel analiz, farklı aksaklık senaryolarında farklı modellerin göreli performansı hakkında değerli içgörüler sunar. Küresel tedarik zinciri ağlarında aksaklıkları yönetmek için etkili stratejilere dair sağladığı içgörülerle, çalışmamız, tedarik zinciri yönetimi alanındaki mevcut literatüre değerli bir katkı sağlamaktadır.

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Lastly, I express my gratitude to all the authors, researchers, and scholars whose works I have cited in this thesis. Their groundbreaking contributions have paved the way for academic progress and have profoundly influenced my perspectives. It is my earnest hope that this thesis will also serve as a meaningful contribution to fellow researchers. With sincere gratitude, I conclude this acknowledgment.

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CHAPTER I

INTRODUCTION

The globalized nature of today's business environment has made supply chain management a critical discipline for organizations searching to maintain a competitive edge. Supply chains include a complex web of interconnected components, within suppliers, production facilities, distribution centers, and customers. However, this complicated network is sensitive to various disruptions that can severely impact its functionality and performance. Factors such as natural disasters, geopolitical instability, and pandemics have the potential to disrupt supply chains, causing significant difficulties for all businesses. These disruptions occur in diverse ways, including the failure or closure of facilities, transportation disruptions, and high demand volatility. Such disruptions can have associated effects throughout the supply chain network, affecting each component in different ways such as shutdowns or permanent closures of facilities. When a facility within a supply chain experiences disruption, customers who were initially assigned to that facility need to be redirected to an operational alternative. Furthermore, this redirection can lead to significant negative consequences, including reduced customer satisfaction, diminished trust and confidence in the company and price surge. Insufficient planning during supply chain recovery can lead to significant damages, particularly in certain cost aspects. Additionally, economic instability can also play a role in causing such disruptions. It leads to fluctuations in demand, supply shortages, currency devaluation, and market uncertainties, all of which add complexity to the recovery process. As a consequence, businesses may face increased lead times, higher inventory carrying costs, reduced profitability, and strained relationships with suppliers and customers. In such situations, the crucial factors for reinforcing the strength of supply network designs are responsiveness and resilience [1]. Moreover, these disruptions interrupt production and the flow of goods and services, leading to delays and potential stock-outs. For instance, certain supply chains have experienced escalated demand for essential items such as facial masks, hand sanitizers, and ventilators, surpassing their capacity to meet such demands. On the other hand, non-essential product supply chains have faced extended production stops [2]. Global disruptions often introduce high demand volatility, characterized by sudden shifts in consumer behavior and market dynamics. For example, during Covid-19 pandemic, certain products have experienced a surge in demand for essential items like personal protective equipment (PPE), ventilators, and dried and canned foods [3]. This demand volatility also generates challenges in terms of forecasting, inventory management, and production planning, as supply chains must rapidly adapt to meet fluctuating customer needs. Moreover, transportation disruptions, including port closures, restrictions on movement, or capacity constraints, further makes it more challenging for supply chain networks. The lack of transporting goods efficiently can disrupt the timely delivery of products, affecting customer satisfaction and increasing costs.

In the face of these disruptions, the primary goal of supply chain management is to mitigate the damaging effects while optimizing the costs and maximizing the service levels. This requires a comprehensive understanding of the challenges which are caused by different disruptions and development of effective strategies to enhance supply chain resilience. To effectively address network risks in supply chain management, it is crucial to understand the significance of solutions and prioritize them accordingly. The successful implementation of solutions for network risks relies on selecting appropriate measures customized to fit the organization's internal and environmental conditions [4]. This strategic execution aligns the organization's capabilities with the specific demands of the market, fostering resilience and adaptability in the face of disruptions, thereby reinforcing its competitive positioning in the business landscape.

This thesis identifies the impacts of global disruptions and their implications for supply chain networks, highlighting the need for effective strategies in supply chain management. Framework of this thesis aims to determine the optimal supply, production, and distribution quantities to ensure adequate demand satisfaction. We first describe our network and disruption types, then we try to determine the main strategic decisions about facility operations using deterministic and scenario-based stochastic models. To understand which model finds out the most cost-efficient decisions, simulation approach is applied to make provisions for the possible disruption scenarios. Hypothesis testing analysis is further employed to compare and determine the cost-efficient model after applying simulation.

To the best of our knowledge, our unique method in addressing this problem involves taking into account multiple disruption types across different echelons and proposing both deterministic and stochastic models. Thus, to assess which model is more favorable in terms of cost performance, comparisons were made through the simulation approach and hypothesis testing. The aim was to identify the model that offers the best balance between cost-effectiveness and accuracy, thereby providing valuable insights for decision-making processes. These innovative aspects distinguish our work and contribute additional perspectives to the existing research. Also, by understanding the various factors that can disrupt supply chains, organizations can enhance their ability to overcome surging times and sustain a competitive advantage in today's dynamic business world.

The subsequent sections of this thesis are structured as follows. Chapter 2 provides a comprehensive review of the related literature, categorized into different subjects. In Chapter 3, the problem description is presented in detail. Chapter 4 introduces the solution approach, which comprises two mathematical models: the deterministic model and the stochastic model. Moving on to Chapter 5, we explain the computational results, starting with the initial problem configuration, followed by data and scenario generation, and concluding with the simulation method along with other subsections. Finally, Chapter 6 concludes the thesis.

CHAPTER II

LITERATURE REVIEW

The field of supply chain management indicated significant attention, particularly in the context of global disruptions and the need for resilience in supply chain networks in recent years. This literature review aims to provide an overview of the current state of research on strategic global supply network planning under disruptions, emphasize the challenges posed by disruptions, exploring the different approaches and methodologies used to address this complex and critical issue in supply chain management with a specific focus on optimizing costs and maximizing service levels in the face of diverse disruptions.

2.1 Supply Chain Resilience and Disruption Management

Supply chain resilience and disruption management have become crucial areas of focus for businesses in today's dynamic and unpredictable environment. Building resilience in supply chains involves implementing strategies and practices that enable businesses to anticipate, absorb, and recover from these disruptions efficiently. By proactively addressing disruptions, organizations can enhance their ability to maintain continuity, minimize the impact of adverse events, and ultimately achieve a more resilient and responsive supply chain network. Here are some related examples to this research, which aims to explore solutions to enhance supply chain resilience and effective disruption management.

[5] discusses the establishment of a data laboratory specifically focused on supply chain response models during epidemic outbreaks. The laboratory aims to explore strategies to effectively manage supply chains during times of crisis, particularly in the context of health epidemics to enhance the resilience and agility of supply chains.

For emphasizing the importance of diversification and redundancy in mitigating disruptions, a portfolio approach was adopted in [6], which accounts supplier failure as a disruption scenario to select the appropriate supplier. Transportation disruptions are handled with some mitigation strategies and ordering policy in a real problem setting to highlight the importance of contingency planning [7], [8]. In the study [9], a dynamic redistribution model was represented for mitigating disruptions during influenza pandemics, focusing on efficient resource allocation. [10] presents a disruption-driven supply chain planning framework that considers proactive and recovery policies to enhance performance under disruptions with using hybrid static-dynamic optimization model. The importance of planning for disruptions in supply chain networks were emphasized in [11] and a risk-based approach was proposed to enhance network resilience with explaining different types of mitigation models such as fortification models. [12] proposes a risk-based approach to enhance network resilience with focusing on a critical inventory planning issue pertaining to emergency response. It is applicable to a wide range of organizations, including those in manufacturing, service etc. that play a crucial role in supplying essential resources for disaster relief operations. Several studies present a multi-objective optimization model for designing resilient supply chain networks, considering disruption risks. [13] introduced a model aimed at designing a multi-commodity supply chain network and the model optimizes two key objectives: cost and demand-weighted connectivity. The exploration of supply chain resilience, considering both single and multiple sourcing, specifically in the context of supplier disruptions, was conducted in [14]. Their study utilized a scenario-based mathematical model to examine the trade-offs and decision-making considerations associated with enhancing supply chain resilience.

2.2 Covid-19 and Pandemics Impact on Supply Chain

With the unprecedented outbreak of COVID-19, supply chains worldwide experienced unprecedented challenges and disruptions. The pandemic's far-reaching impact exposed vulnerabilities and weaknesses in global supply chain networks, affecting industries ranging from healthcare and pharmaceuticals to retail and manufacturing. These are triggered a significant body of research. Below are some relevant examples related to this research.

The article [15] examines the optimization of supply chain networks during the COVID-19 pandemic, considering the critical role of labor. It investigates strategies to minimize labor shortages as disruptions and optimize resource allocation during labor-related challenges. [16] inspects the specific case of toilet paper supply chains during the COVID-19 crisis and examines the strategies employed by retailers and manufacturers to manage disruptions with some production strategies such as, sharing resources among manufacturers, using backup suppliers, producing basic items, packing products in the minimum sizes and mitigate shortages due to the demand volatility. Also, in another study [17], production recovery plan is presented for high-demand items in general during the COVID-19 pandemic, optimizing production in the face of high demand volatility. The article [18] proposes a decision support system for demand management in healthcare supply chains, focusing on epidemic outbreaks and provides insights into demand management strategies for the disruption of demand volatility. [19] proposes a supply chain disruption risk mitigation model to effectively manage the risks associated with the pandemic. As a disruption type, suppliers and retailers are available and unavailable in random periods and they focused on mitigation strategies to enhance supply chain resilience with using some heuristic algorithms, during the COVID-19 pandemic. As a specific supply chain, [20] investigated the food supply chain, focusing on the challenges faced by the food industry during times of crisis with using a solution approach; simulation model to consider different scenarios occurred in this type of supply chain. In [21] a simulation model is also used and considered three specific scenarios which are about epidemic's effects to China producer regions, DCs and customers respectively to enhance resilience in supply chains.

2.3 Supply Chain Network Design and Optimization

This crucial area of study focuses on strategically configuring supply chain networks to achieve maximum efficiency and cost-effectiveness. This field involves making critical decisions related to the location of facilities, distribution centers, and warehouses, as well as determining optimal transportation routes and inventory levels. By leveraging advanced modeling and optimization techniques, businesses can design supply chain networks that can adapt to changing market demands, minimize operational costs, and enhance overall performance. In connection with this research, we have identified several related examples.

In study [22], also introduces a scenario-based supply chain network risk modeling approach and Monte-Carlo approach is applied for the possible future scenarios. As a different objective assessment, the design of retail supply chain networks under operational and disruption risks is addressed in [23], offering insights into the integration of resilience capabilities. With minimizing the total number of required supply facilities and required number of vehicles of each transportation mode, supplier and transportation disruption are considered. Both [24] and [25] adopted a two-stage stochastic programming framework to integrate uncertainties into the decision-making process. In tackling the reliable facility location problem, [24] employed the sample average approximation (SAA) algorithm as a solution approach. Meanwhile, [25] focused on implementing multiple resilience strategies, including facility fortification, inventory prepositioning, and reserved capacity, within the retail supply chain network design. By incorporating these strategies, the studies aimed to enhance the resilience of the supply chain and effectively manage disruptions arising from uncertain conditions. After this framework, lagrangian relaxation is applied as a solution approach to determine facility location decisions and lateral transshipment quantities across different disruption scenarios with a real-world application in [26]. In the study [27], the factors influencing resilient supply chain design through the utilization of Monte Carlo simulation are examined. The researchers emphasized the significance of considering multiple factors when designing resilient supply chains. Initially, they focused on maximizing profit under different demand conditions by developing a mathematical model. Subsequently, they employed a simulation model to incorporate the effects of facility disruptions. By integrating these approaches, the study aimed to provide insights into the design of resilient supply chains that can effectively manage disruptions while optimizing profitability.

The classification of literature, as presented in Table 1, categorizes the articles based on their subjects and solution methods, allowing for a comprehensive understanding of the strategies employed to enhance supply chain resilience under disruptive scenarios.

Table 1: Classification of Literature

Subjects	**Articles**
Supply Chain Resilience and Disruption Management	[5],[6], [7], [8],[9], [10], [11], [12], [13], [14]
Covid-19 and Pandemics Impact on Supply Chain	[5], [15], [16], [17], [18], [19],[20], [21]
Supply Chain Network Design and Optimization	[22], [23], [24],[25],[26],[27]
Solution Methods	**Articles**
Simulation Methods	[9], [10], [16], [20],[21], [27]
Mathematical Model with some Approaches	[5], [9], [12],[13], [14], [15],[17], [22], [23]
Two-stage stochastic programming	[24], [25]
Monte Carlo Approach	[22], [27]
Mitigation Strategies	[7], [11], [19]
Lagrangian Relaxation	[26]
Heuristics and Other Approaches	[6],[8], [18]

These articles highlight the diverse aspects of managing disruptions in supply chain networks during the epidemic. They delve into optimization models, strategies for specific product categories, risk mitigation approaches, and the costs and trade-offs involved in designing resilient supply chains. By incorporating the findings and methodologies presented in these articles, organizations can enhance their ability to navigate disruptions effectively, minimize costs, and maximize service levels within their supply chain networks. While existing literature has examined different dimensions of supply chain disruptions, this thesis aims to provide a unique contribution by concentrating on multiple disruption scenarios. We employ both a deterministic model and a scenario-based model to optimize supply chain networks and make critical decisions. Our scenario-based model can be classified into the framework of two-stage stochastic programming. This is due to its objective of minimizing fixed costs associated with scenario-independent decisions like opening, operating, and closing facilities. These strategic decisions are followed by the assessment of expected costs for other network-related decisions, including procurement, production, distribution, and inventory management. By delving into this specific approach, we aim to provide novel insights and practical solutions that address the complexities arising from diverse disruptions in supply chain management. Also, the aim of this thesis is to investigate the procurement, distribution, production, and demand satisfaction challenges arising from disruptions in global supply chain networks and propose practical strategies to mitigate their impacts. Through the implementation of scenario-based optimization, this research wants to enhance the resilience and efficiency of supply chains, considering the challenges posed by disruptions in today's dynamic business environment. Subsequently, simulation techniques are applied to evaluate and refine the decision-making process, aiming to align the models' outcomes with real-world disruption scenarios. This approach allows for an analysis of the most cost-effective decisions in addressing disruptions within the supply chain network.

CHAPTER III

PROBLEM DESCRIPTION

In this thesis we focus on addressing the global supply network planning problem under disruptions. In supply chain networks, there are complex and interconnected systems that involve multiple entities, including suppliers, manufacturers, distributors, and customers. The efficient functioning of these networks is essential for meeting customer demands, and achieving business objectives. However, in real-world scenarios, supply chain networks are susceptible to various disruptions, which can significantly impact their performance and resilience. These disruptions can arise from a diverse range of factors, including natural disasters, geopolitical uncertainties, economic fluctuations, public health crises, among others. Such disruptions can result in inventory shortages, production delays, facility breakdowns, increased costs, and reduced customer satisfaction. In this study, we examine two types of disruptions: facility failures and demand volatility. Facility failures can be classified into different states, including “zero” capacity, representing a total breakdown, and “half” capacity, indicating reduced production or inventory due to disruption effects. Similarly, customer demand can vary based on the impact of disruptions, with “high” demand during urgent situations and “low” demand for certain products due to prioritization of other critical needs in disaster environments.

In these circumstances, considering the complexity and dynamic nature of supply chain networks, efficiently managing and mitigating disruptions is of primary importance. To address this issue, this thesis aims to propose effective strategies and models that can enhance the resilience and adaptability of global supply networks in the face of disruptions. We will analyze and evaluate the consequences of multiple types of disruptions within a finite planning horizon segmented into discrete time periods. By understanding the consequences of disruptions on various aspects of the supply chain, our aim is to create resilient and proactive strategies that ensure uninterrupted operations, minimize losses, and uphold customer satisfaction, even in challenging and unpredictable circumstances. For this, we examine the network design of a generic supply chain with multi-echelons, as illustrated in Figure 1.

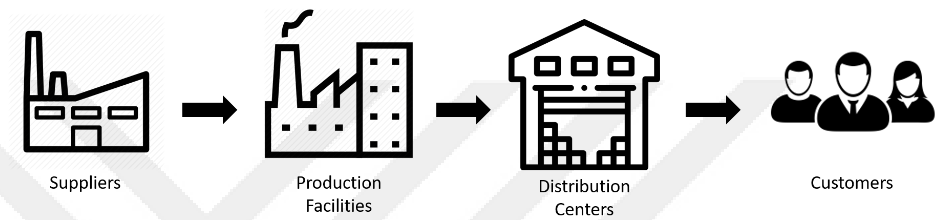

Figure 1: Multi-Echelon Supply Chain Network

In this problem, a set of raw materials, R, are procured from a set of suppliers, S, and these raw materials are shipped to a set of production facilities, I, for manufacturing various set of product types, J, using the acquired raw materials, served to a set of distribution centers, K, which are intermediaries to facilitate distribution of the product from the production facilities to a set of customers, C, and customer demands vary across different product types besides, can only be serviced by distribution centers in a set of determined time periods, T. Moreover, the consideration of inventory is limited to the production facilities for both raw materials and product types, as well as in distribution centers exclusively for product types.

In the supply chain management, another critical aspect of strategic decision making is cost optimization. The primary goal is to minimize expenses at various stages of the supply chain while maintaining the desired level of performance and resilience. This involves making prudent choices regarding procurement, production, inventory management, transportation, distribution and demand satisfaction. For this problem and to address these situations, optimal strategic decisions for the supply chain network which are open, operate and close with other optimal decisions related to procurement, production, distribution, and demand satisfaction are determined using Mixed-Integer Linear Programming (MILP) models which are explained in the following section titled “Solution Approach”.

CHAPTER IV

SOLUTION APPROACH

This chapter explores the application of two distinct Mixed Integer Linear Programming models as a solution strategy within the context of the discussed problem. In this thesis, MILPs aim to empower the identification of optimal strategic decisions, focusing on operating, opening, and closing decisions exclusively for the production facilities and distribution centers besides the other network decisions that are procurement, production, distribution, and demand satisfaction.

To ensure the alignment of our problem's solution methodology with real-life situations, we adopt a simulation approach which is explained in the next chapter. Our objective is to effectively utilize both models and facilitate a meaningful comparison of their performance based on associated costs. By carefully employing these models, we aim to conduct a comprehensive evaluation of their respective performances, allowing us to derive valuable insights and make well-informed decisions concerning cost-effectiveness for our problem.

4.1 Mathematical Model

The underlying MILP models incorporate deterministic and stochastic programming techniques respectively and both are for the consideration of disruption scenarios and their associated risks in different ways. Both mathematical models are subject to important analysis aimed at minimizing the overall costs within the framework. Furthermore, the optimization of these models yields invaluable insights into the interconnect trade-offs between cost, performance, and resilience. The objective is to identify the model that encompasses the most cost-effective decisions for the supply chain networks.

By leveraging the insights gained from the literature review, the Mathematical Programming provides a solid foundation for this problem and especially for the global supply chain networks, enables effective decision-making and proactive management of disruptions. In this thesis, MILP models, named as MM1 and MM2. MM1 represents a deterministic model and MM2 is a stochastic model. The following sections provide the details for these two models.

4.1.1 Deterministic Model

Regarding supply chain network decisions, the deterministic model aims to optimize overall costs by considering various scenarios in a straightforward manner, relying on expected values as input. The expected values are computed by multiplying the probabilities of different disruption cases with the corresponding quantities of scenarios, in the absence of any disruptions, thus, the overall facilities' capacity and customers' demand amounts. In this way, the model calculates the anticipated values, taking into consideration the likelihood of each disruption scenario and its impact on the capacities of facilities and the demands of customers. Consequently, the deterministic model proves to be a viable option for determining the values of decision variables in this domain. Table 2 outlines the sets, parameters, and decision variables of the deterministic model.

The parameters included in this model pertain to various aspects of supply chain costs, including procurement, production, transportation, storage, penalty, backorder, as well as fixed cost types relevant to production facilities and distribution centers. The aim of the model is to minimize these costs through the formulation of an objective function. As for capacity and demand parameters, deterministic modeling utilizes their expected values. Based on the specified costs and other relevant parameters, the model's objective function and constraints are established as follows:

Table 2: Nomenclature for Deterministic Model (MM1)

Sets	
S	Set of suppliers – indexed by s
I	Set of production facilities – indexed by i
K	Set of distribution centers – indexed by k
C	Set of customer locations – indexed by c
T	Set of time periods – indexed by t
J	Set of product types – indexed by j
R	Set of raw materials – indexed by r
Parameters	
pr_{rs}	Unit procurement cost of raw material r from supplier s to production facility
pd_{ji}	Unit production cost of product type j in production facility i
g_{jik}	Unit transportation cost of product type j from production facility i to DC k
h_{jkc}	Unit transportation cost of product type j from DC k to customer location c
sc_{ji}	Unit storage cost of product type j in production facility i
sr_{ri}	Unit storage cost of raw material r in production facility i
sp_{jk}	Unit storage cost of product type j in DC k
p_{jc}	Unit penalty cost of unsatisfied demand of product type j in customer location c
b_{jc}	Unit backorder cost of product type j in customer location c
bc_{jc}	Backorder time amount of product type j in customer location c
OC_i	Fixed cost for operating a production facility i
O_i	Fixed cost for opening a production facility i
C_i	Fixed cost for closing a production facility i
PL_k	Fixed cost for operating a DC k
OP_k	Fixed cost for opening a DC k
CL_k	Fixed cost for closing a DC k
$caps_{srt}$	Expected capacity of supplier s for raw material r at period t
cap_{ijt}	Expected capacity of production facility i for product type j at period t
$capd_{kjt}$	Expected capacity of each DC k for product type j at period t
d_{cjt}	Expected demand of customer location c for product type j at period t
IR_{ri0}	Initial inventory amount of raw material r in production facility i
I_{ji0}	Initial inventory amount of product type j in production facility i
ID_{jk0}	Initial inventory amount of product type j in DC k
β_{ji}	Capacity consumption amount of product type j of production facility i
α_{rj}	Amount of raw material r needed to produce one product type j
M	Arbitrarily large constant
Decision variables	
F_{it}	1, if production facility i is operated at period t, 0 otherwise
FO_{it}	1, if an inactive production facility i is opened at period t, 0 otherwise
FC_{it}	1, if an active production facility i is closed at period t, 0 otherwise
L_{kt}	1, if DC k is operated at period t, 0 otherwise
LO_{kt}	1, if an inactive DC k is opened at period t, 0 otherwise
LC_{kt}	1, if an active DC k is operated at period t, 0 otherwise
X_{rsit}	Amount of raw material r procured from supplier s for production facility i at period t
Y_{jit}	Amount of product type j produced by production facility i at period t
Z_{jikt}	Amount of product type j transferred from production facility i to DC k at period t
$D_{jkctt'}$	Amount of product type j distributed from DC k to customer location c in period t' to satisfy demand at period t
I_{jit}	Amount of inventory level of product type j in production facility i at the end of period t
IR_{rit}	Amount of inventory level of raw material r in production facility i at the end of period t
ID_{jkt}	Amount of inventory level of product type j in DC k at the end of period t
LS_{jct}	Amount of penalty for product type j in customer location c at period t

$$\min \quad \sum_{j,c,t} p_{jc} LS_{jct} + \sum_{j,k,c,t} \sum_{t'>t} b_{jc} D_{jkctt'} + \sum_{r,s,i,t} pr_{rs} X_{rsit} + \sum_{j,i,t} pd_{ji} Y_{jit} + \sum_{j,i,k,t} g_{jik} Z_{jikt} + \sum_{j,k,c,t} \sum_{t \le t'} h_{jkc} D_{jkctt'}$$
$$+ \sum_{j,i,t} sc_{ji} I_{jit} + \sum_{j,k,t} sp_{jk} ID_{jkt} + \sum_{r,i,t} sr_{ri} IR_{rit} + \sum_{i,t} OC_i F_{it} + \sum_{i,t} O_i FO_{it} + \sum_{i,t} C_i FC_{it} + \sum_{k,t} PL_k L_{kt}$$
$$+ \sum_{k,t} OP_k LO_{kt} + \sum_{k,t} CL_k LC_{kt} \tag{1}$$

$$\text{s.t.} \quad \sum_i X_{rsit} \le caps_{srt} \qquad \forall s \in \mathcal{S}, \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \tag{2}$$
$$IR_{ri0} + \sum_s X_{rsit} = \sum_j \alpha_{rj} Y_{jit} + IR_{rit} \qquad \forall r \in \mathcal{R}, \forall i \in \mathcal{I}, t = 1 \tag{3}$$
$$IR_{ri(t-1)} + \sum_s X_{rsit} = \sum_j \alpha_{rj} Y_{jit} + IR_{rit} \qquad \forall r \in \mathcal{R}, \forall i \in \mathcal{I}, t > 1 \tag{4}$$
$$I_{ji0} + Y_{jit} = \sum_k Z_{jikt} + I_{jit} \qquad \forall j \in \mathcal{J}, \forall i \in \mathcal{I}, t = 1 \tag{5}$$
$$I_{ji(t-1)} + Y_{jit} = \sum_k Z_{jikt} + I_{jit} \qquad \forall i \in \mathcal{I}, \forall j \in \mathcal{J}, t > 1 \tag{6}$$
$$\beta_{ji} Y_{jit} \le cap_{ijt} * F_{it} \qquad \forall i \in \mathcal{I}, \forall j \in \mathcal{J}, \forall t \in \mathcal{T} \tag{7}$$
$$ID_{jk0} + \sum_i Z_{jikt} = \sum_c D_{jkctt'} + ID_{jkt} \qquad \forall j \in \mathcal{J}, \forall k \in \mathcal{K}, t = 1 \tag{8}$$
$$ID_{jk(t-1)} + \sum_i Z_{jikt} = \sum_c \sum_{\tau \le t} D_{jkc\tau tn} + ID_{jkt} \qquad \forall j \in \mathcal{J}, \forall k \in \mathcal{K}, t > 1 \tag{9}$$
$$ID_{jkt} \le capd_{kjt} \qquad \forall j \in \mathcal{J}, \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \tag{10}$$
$$\sum_k \sum_{t'=t}^{t+bc_{jc}} D_{jkctt'} + LS_{jct} = d_{cjt} \qquad \forall j \in \mathcal{J}, \forall c \in \mathcal{C}, \forall t \in \mathcal{T} \tag{11}$$
$$FO_{it} \le F_{it} \qquad \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \tag{12}$$
$$FC_{it} \ge F_{i(t-1)} - F_{it} \qquad \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \tag{13}$$
$$FO_{it} \ge F_{it} - F_{i(t-1)} \qquad \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \tag{14}$$
$$LO_{kt} \le L_{kt} \qquad \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \tag{15}$$
$$LC_{kt} \ge L_{k(t-1)} - L_{kt} \qquad \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \tag{16}$$
$$LO_{kt} \ge L_{kt} - L_{k(t-1)} \qquad \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \tag{17}$$
$$X_{rsit} \le M * F_{it} \qquad \forall r \in \mathcal{R}, \forall s \in \mathcal{S}, \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \tag{18}$$
$$Z_{jikt} \le M * F_{it} \qquad \forall j \in \mathcal{J}, \forall i \in \mathcal{I}, \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \tag{19}$$
$$D_{jkctt'} \le M * L_{kt} \qquad \forall j \in \mathcal{J}, \forall k \in \mathcal{K}, \forall c \in \mathcal{C}, \forall t \in \mathcal{T}, \forall t' \in \mathcal{T} \tag{20}$$
$$Z_{jikt} \le M * L_{kt} \qquad \forall j \in \mathcal{J}, \forall i \in \mathcal{I}, \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \tag{21}$$
$$F_{it}, FO_{it}, FC_{it} \in \{0, 1\} \qquad \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \tag{22}$$
$$L_{kt}, LO_{kt}, LC_{kt} \in \{0, 1\} \qquad \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \tag{23}$$
$$X_{rsit} \ge 0 \qquad \forall r \in \mathcal{R}, \forall s \in \mathcal{S}, \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \tag{24}$$
$$Y_{jit} \ge 0 \qquad \forall j \in \mathcal{J}, \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \tag{25}$$
$$Z_{jikt} \ge 0 \qquad \forall j \in \mathcal{J}, \forall i \in \mathcal{I}, \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \tag{26}$$

$$D_{jkctt'} \geq 0 \qquad \forall j \in \mathcal{J}, \forall k \in \mathcal{K}, \forall c \in \mathcal{C}, \forall t \in \mathcal{T}, \forall t' \in \mathcal{T} \quad (27)$$

$$IR_{rit} \geq 0 \qquad \forall r \in \mathcal{R}, \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \quad (28)$$

$$I_{jit} \geq 0 \qquad \forall j \in \mathcal{J}, \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \quad (29)$$

$$ID_{jkt} \geq 0 \qquad \forall j \in \mathcal{J}, \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \quad (30)$$

$$LS_{jct} \geq 0 \qquad \forall j \in \mathcal{J}, \forall c \in \mathcal{C}, \forall t \in \mathcal{T} \quad (31)$$

The objective function (1) minimizes the total cost by considering penalties per unit for lost sales, backorders, procurement, production, transportation, storage, operating, opening, and closing costs. Constraints (2) ensure that the total procurement of raw materials from all suppliers for each production facility in each period $t \in T$ does not exceed the suppliers' capacity. Constraints (3) and (4) represent the inventory balance between procurement and production in the production facilities. Constraints (5) and (6) represent the inventory balance between the production facilities and the distribution centers (DCs). Constraints (7) indicate capacity constraints on each production facility. Constraints (8) and (9) represent the flow balance between the DCs and the customers. Constraints (10) ensure that the inventory level in the DCs does not exceed their capacity. Constraints (11) guarantee that customer demand is satisfied. Constraints (12), (13), and (14) determine whether a production facility should be operated, opened if, or closed if not. Constraints (15), (16), and (17) determine whether a DC should be operated, opened if, or closed if not. Constraints (18) and (19) are Big-M constraints that allow a production facility to produce and send a specific amount if it is decided to be operated. Constraints (20) and (21) are Big-M constraints that enable a DC to procure and send a specific amount if it is decided to be operated. Finally, constraints (22), (23) are integrity constraints and (24), (25), (26), (27), (28), (29), (30) and (31) are non-negativity constraints.

4.1.2 Stochastic Model

In the second MILP model, known as the stochastic model, considers various scenarios and makes scenario based decisions while minimizing the expected total costs. Despite potential complexities and implementation challenges for companies, it tries to offer the advantage of identifying cost-efficient decisions by considering various disruption scenarios. Consequently, companies can enhance their preparedness to manage specific types of disruptions outlined in the problem through effective strategic and primary network decisions. Table 3 presents an outline of the sets, parameters, and decision variables associated with the stochastic model. This model also can provide significant findings to inform decision-making processes in numerous ways, as it considers a diverse array of potential scenarios and their corresponding outcomes.

The main distinction between the deterministic model and the stochastic model lies in their approach to handling disruption cases. The deterministic model employs expected capacity and expected demand values to make decisions, while the stochastic model considers scenario-based decisions based on the probabilities of each scenario. Deterministic model's approach offers a more straightforward and easier implementation compared to the following stochastic model. The objective of the stochastic model is aiming to minimize expected costs associated with strategic and network decisions by formulating an appropriate objective function. Detailed explanations regarding the implementation of parameters can be found in the computational results' data and scenario generation section. Considering the specified objectives and various parameters, the objective function and constraints of the stochastic model are established as follows:

Table 3: Nomenclature for Stochastic Model (MM2)

Sets	
S	Set of suppliers – indexed by s
I	Set of production facilities – indexed by i
K	Set of distribution centers – indexed by k
C	Set of customer locations– indexed by c
T	Set of time periods – indexed by t
J	Set of product types – indexed by j
R	Set of raw materials – indexed by r
N	Set of scenarios – indexed by n
Parameters	
pr_{rs}	Unit procurement cost of raw material r from supplier s to production facility
pd_{ji}	Unit production cost of product type j in production facility i
g_{jik}	Unit transportation cost of product type j from production facility i to DC k
h_{jkc}	Unit transportation cost of product type j from DC k to customer location c
sc_{ji}	Unit storage cost of product type j in production facility i
sr_{ri}	Unit storage cost of raw material r in production facility i
sp_{jk}	Unit storage cost of product type j in DC k
p_{jc}	Unit penalty cost of unsatisfied demand of product type j in customer location c
b_{jc}	Unit backorder cost of product type j in customer location c
bc_{jc}	Backorder time amount of product type j in customer location c
OC_i	Fixed cost for operating a production facility i
O_i	Fixed cost for opening a production facility i
C_i	Fixed cost for closing a production facility i
PL_k	Fixed cost for operating a DC k
OP_k	Fixed cost for opening a DC k
CL_k	Fixed cost for closing a DC k
$caps_{nsrt}$	Capacity of supplier s for raw material r at period t under scenario n
cap_{nijt}	Capacity of production facility i for product type j at period t under scenario n
$capd_{nkjt}$	Capacity of each DC k for product type j at period t under scenario n
d_{ncjt}	Demand of customer location c for product type j at period t under scenario n
IR_{ri0}	Initial inventory amount of raw material r in production facility i
I_{ji0}	Initial inventory amount of product type j in production facility i
ID_{jk0}	Initial inventory amount of product type j in DC k
β_{ji}	Capacity consumption amount of product type j of production facility i
α_{rj}	Amount of raw material r needed to produce one product type j
π_n	Probability of occurrence of scenario n
M	Arbitrarily large constant
Decision variables	
F_{it}	1, if production facility i is operated at period t, 0 otherwise
FO_{it}	1, if an inactive production facility i is opened at period t, 0 otherwise
FC_{it}	1, if an active production facility i is closed at period t, 0 otherwise
L_{kt}	1, if DC k is operated at period t, 0 otherwise
LO_{kt}	1, if an inactive DC k is opened at period t, 0 otherwise
LC_{kt}	1, if an active DC k is operated at period t, 0 otherwise
X_{rsitn}	Amount of raw material r procured from supplier s for production facility i at period t under scenario n
Y_{jitn}	Amount of product type j produced by production facility i at period t under scenario n
Z_{jiktn}	Amount of product type j transferred from production facility i to DC k at period t under scenario n
$D_{jkctt'n}$	Amount of product type j distributed from DC k to customer location c in period t' to satisfy demand at period t under scenario n
I_{jitn}	Amount of inventory level of product type j in production facility i at the end of period t under scenario n
IR_{ritn}	Amount of inventory level of raw material r in production facility i at the end of period t under scenario n
ID_{jktn}	Amount of inventory level of product type j in DC k at the end of period t under scenario n
LS_{jctn}	Amount of penalty for product type j in customer location c at period t under scenario n

$$\begin{aligned}\min \quad & \sum_n \pi_n \Bigg(\sum_{j,c,t} p_{jc} LS_{jctn} + \sum_{j,k,c,t} \sum_{t'>t} b_{jc} D_{jkctt'n} + \sum_{r,s,i,t} pr_{rs} X_{rsitn} + \sum_{j,i,t} pd_{ji} Y_{jitn} \\ & + \sum_{j,i,k,t} g_{jik} Z_{jiktn} + \sum_{j,k,c,t} \sum_{t \le t'} h_{jkc} D_{jkctt'n} + \sum_{j,i,t} sc_{ji} I_{jitn} + \sum_{j,k,t} sp_{jk} ID_{jktn} + \sum_{r,i,t} sr_{ri} IR_{ritn} \Bigg) \\ & + \sum_{i,t} OC_i F_{it} + \sum_{i,t} O_i FO_{it} + \sum_{i,t} C_i FC_{it} + \sum_{k,t} PL_k L_{kt} + \sum_{k,t} OP_k LO_{kt} + \sum_{k,t} CL_k LC_{kt}\end{aligned} \tag{32}$$

s.t.

$$\sum_i X_{rsitn} \le caps_{srtn} \qquad \forall s \in \mathcal{S}, \forall r \in \mathcal{R}, \forall t \in \mathcal{T}, \forall n \in \mathcal{N} \tag{33}$$

$$IR_{ri0} + \sum_s X_{rsitn} = \sum_j \alpha_{rj} Y_{jitn} + IR_{ritn} \qquad \forall r \in \mathcal{R}, \forall i \in \mathcal{I}, \forall n \in \mathcal{N}, t = 1 \tag{34}$$

$$IR_{ri(t-1)n} + \sum_s X_{rsitn} = \sum_j \alpha_{rj} Y_{jitn} + IR_{ritn} \qquad \forall r \in \mathcal{R}, \forall i \in \mathcal{I}, \forall n \in \mathcal{N}, t > 1 \tag{35}$$

$$I_{ji0} + Y_{jitn} = \sum_k Z_{jiktn} + I_{jitn} \qquad \forall j \in \mathcal{J}, \forall i \in \mathcal{I}, \forall n \in \mathcal{N}, t = 1 \tag{36}$$

$$I_{ji(t-1)n} + Y_{jitn} = \sum_k Z_{jiktn} + I_{jitn} \qquad \forall i \in \mathcal{I}, \forall j \in \mathcal{J}, \forall n \in \mathcal{N}, t > 1 \tag{37}$$

$$\beta_{ji} Y_{jitn} \le cap_{ijtn} * F_{it} \qquad \forall i \in \mathcal{I}, \forall j \in \mathcal{J}, \forall t \in \mathcal{T}, \forall n \in \mathcal{N} \tag{38}$$

$$ID_{jk0} + \sum_i Z_{jiktn} = \sum_c D_{jkctt'n} + ID_{jktn} \qquad \forall j \in \mathcal{J}, \forall k \in \mathcal{K}, \forall n \in \mathcal{N}, t = 1 \tag{39}$$

$$ID_{jk(t-1)n} + \sum_i Z_{jiktn} = \sum_c \sum_{\tau \le t} D_{jkc\tau tn} + ID_{jktn} \qquad \forall j \in \mathcal{J}, \forall k \in \mathcal{K}, \forall n \in \mathcal{N}, t > 1 \tag{40}$$

$$ID_{jktn} \le capd_{kjtn} \qquad \forall j \in \mathcal{J}, \forall k \in \mathcal{K}, \forall t \in \mathcal{T}, \forall n \in \mathcal{N} \tag{41}$$

$$\sum_k \sum_{t'=t}^{t+bc_{jc}} D_{jkctt'n} + LS_{jctn} = d_{cjtn} \qquad \forall j \in \mathcal{J}, \forall c \in \mathcal{C}, \forall t \in \mathcal{T}, \forall n \in \mathcal{N} \tag{42}$$

$$FO_{it} \le F_{it} \qquad \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \tag{43}$$

$$FC_{it} \ge F_{i(t-1)} - F_{it} \qquad \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \tag{44}$$

$$FO_{it} \ge F_{it} - F_{i(t-1)} \qquad \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \tag{45}$$

$$LO_{kt} \le L_{kt} \qquad \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \tag{46}$$

$$LC_{kt} \ge L_{k(t-1)} - L_{kt} \qquad \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \tag{47}$$

$$LO_{kt} \ge L_{kt} - L_{k(t-1)} \qquad \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \tag{48}$$

$$X_{rsitn} \le M * F_{it} \qquad \forall r \in \mathcal{R}, \forall s \in \mathcal{S}, \forall i \in \mathcal{I}, \forall t \in \mathcal{T}, \forall n \in \mathcal{N} \tag{49}$$

$$Z_{jiktn} \le M * F_{it} \qquad \forall j \in \mathcal{J}, \forall i \in \mathcal{I}, \forall k \in \mathcal{K}, \forall t \in \mathcal{T}, \forall n \in \mathcal{N} \tag{50}$$

$$D_{jkctt'n} \le M * L_{kt} \qquad \forall j \in \mathcal{J}, \forall k \in \mathcal{K}, \forall c \in \mathcal{C}, \forall t \in \mathcal{T}, \forall t' \in \mathcal{T}, \forall n \in \mathcal{N} \tag{51}$$

$$Z_{jiktn} \le M * L_{kt} \qquad \forall j \in \mathcal{J}, \forall i \in \mathcal{I}, \forall k \in \mathcal{K}, \forall t \in \mathcal{T}, \forall n \in \mathcal{N} \tag{52}$$

$$F_{it}, FO_{it}, FC_{it} \in \{0,1\} \qquad \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \tag{53}$$

$$L_{kt}, LO_{kt}, LC_{kt} \in \{0,1\} \qquad \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \tag{54}$$

$$X_{rsitn} \ge 0 \qquad \forall r \in \mathcal{R}, \forall s \in \mathcal{S}, \forall i \in \mathcal{I}, \forall t \in \mathcal{T}, \forall n \in \mathcal{N} \tag{55}$$

$$Y_{jitn} \ge 0 \qquad \forall j \in \mathcal{J}, \forall i \in \mathcal{I}, \forall t \in \mathcal{T}, \forall n \in \mathcal{N} \tag{56}$$

$$Z_{jiktn} \geq 0 \qquad \forall j \in \mathcal{J}, \forall i \in \mathcal{I}, \forall k \in \mathcal{K}, \forall t \in \mathcal{T}, \forall n \in \mathcal{N} \quad (57)$$

$$D_{jkctt'n} \geq 0 \qquad \forall j \in \mathcal{J}, \forall k \in \mathcal{K}, \forall c \in \mathcal{C}, \forall t \in \mathcal{T}, \forall t' \in \mathcal{T}, \forall n \in \mathcal{N} \quad (58)$$

$$IR_{ritn} \geq 0 \qquad \forall r \in \mathcal{R}, \forall i \in \mathcal{I}, \forall t \in \mathcal{T}, \forall n \in \mathcal{N} \quad (59)$$

$$I_{jitn} \geq 0 \qquad \forall j \in \mathcal{J}, \forall i \in \mathcal{I}, \forall t \in \mathcal{T}, \forall n \in \mathcal{N} \quad (60)$$

$$ID_{jktn} \geq 0 \qquad \forall j \in \mathcal{J}, \forall k \in \mathcal{K}, \forall t \in \mathcal{T}, \forall n \in \mathcal{N} \quad (61)$$

$$LS_{jctn} \geq 0 \qquad \forall j \in \mathcal{J}, \forall c \in \mathcal{C}, \forall t \in \mathcal{T}, \forall n \in \mathcal{N} \quad (62)$$

The objective function (32) minimizes the total expected cost by considering penalties for lost-sales, backorders, procurement, production, transportation, storage, operating, opening, and closing costs. Constraints (33) ensure that the total procurement of raw materials from all suppliers for each production facility in each period $t \in T$ under scenario $n \in N$ does not exceed the suppliers' capacity. Constraints (34) and (35) represent the inventory balance between procurement and production in the production facilities. Constraints (36) and (37) represent the inventory balance between the production facilities and the distribution centers (DCs). Constraints (38) indicate capacity constraints on each production facility. Constraints (39) and (40) represent the flow balance between the distribution centers and the customers. Constraints (41) ensure that the inventory level in the distribution centers does not exceed their capacity. Constraints (42) guarantee that customer demand is satisfied. Constraints (43), (44), and (45) determine whether a production facility should be operated, opened if, or closed if not. Constraints (46), (47), and (48) determine whether a DC should be operated, opened if, or closed if not. Constraints (49) and (50) are Big-M constraints that allow a production facility to produce and send a specific amount if it is decided to be operated. Constraints (51) and (52) are Big-M constraints that enable a the distribution center to procure and send a specific amount if it is decided to be operated. Finally, constraints (53) and (54) are integrity constraints, which ensure that the these decision variables are binary and (55), (56), (57), (58), (59), (60), (61) and (62) are non-negativity constraints.

The comparison of the complexity of MILP approaches is presented in Table 4 and Table 5. The number of decision variables and constraints for each model is calculated based on their respective cardinalities.

Table 4: Number of Decision Variables

Decision Variables	**MM1**	**MM2**
Binary Decisions (open, operate, close)	$(\lvert I\rvert + \lvert K\rvert) \times \lvert T\rvert$	$(\lvert I\rvert + \lvert K\rvert) \times \lvert T\rvert$
Inventory	$\lvert T\rvert \times (\lvert J\rvert \times \lvert I\rvert + \lvert R\rvert \times \lvert I\rvert + \lvert J\rvert \times \lvert K\rvert)$	$\lvert T\rvert \times \lvert N\rvert \times (\lvert J\rvert \times \lvert I\rvert + \lvert R\rvert \times \lvert I\rvert + \lvert J\rvert \times \lvert K\rvert)$
Production	$\lvert I\rvert \times \lvert J\rvert \times \lvert T\rvert$	$\lvert I\rvert \times \lvert J\rvert \times \lvert T\rvert \times \lvert N\rvert$
Procurement	$\lvert R\rvert \times \lvert S\rvert \times \lvert I\rvert \times \lvert T\rvert$	$\lvert R\rvert \times \times \lvert S\rvert \times \lvert I\rvert \times \lvert T\rvert \times \lvert N\rvert$
Transportation	$\lvert J\rvert \times \lvert I\rvert \times \lvert K\rvert \times \lvert T\rvert$	$\lvert J\rvert \times \lvert I\rvert \times \lvert K\rvert \times \lvert T\rvert \times \lvert N\rvert$
Demand Satisfaction	$\lvert J\rvert \times \lvert K\rvert \times \lvert C\rvert \times \lvert T\rvert^2$	$\lvert J\rvert \times \lvert K\rvert \times \lvert C\rvert \times \lvert T\rvert^2 \times \lvert N\rvert$
Lost Sale	$\lvert J\rvert \times \lvert C\rvert \times \lvert T\rvert$	$\lvert J\rvert \times \lvert C\rvert \times \lvert T\rvert \times \lvert N\rvert$

Table 5: Number of Constraints

Constraints	**MM1**	**MM2**
Inventory Balance	$\lvert T\rvert \times (\lvert J\rvert \times \lvert I\rvert + \lvert R\rvert \times \lvert I\rvert + \lvert J\rvert \times \lvert K\rvert)$	$\lvert T\rvert \times \lvert N\rvert \times (\lvert J\rvert \times \lvert I\rvert + \lvert R\rvert \times \lvert I\rvert + \lvert J\rvert \times \lvert K\rvert)$
Facility Operating	$(\lvert I\rvert \times \lvert T\rvert)^3 + (\lvert K\rvert \times \lvert T\rvert)^3$	$\lvert I\rvert \times \lvert T\rvert \times \lvert N\rvert$
Capacity	$\lvert T\rvert \times (\lvert S\rvert \times \lvert R\rvert + \lvert I\rvert \times \lvert J\rvert + \lvert J\rvert \times \lvert C\rvert)$	$\lvert N\rvert \times \lvert T\rvert \times (\lvert S\rvert \times \lvert R\rvert + \lvert I\rvert \times \lvert J\rvert + \lvert J\rvert \times \lvert C\rvert)$
Demand Satisfaction	$\lvert J\rvert \times \lvert C\rvert \times \lvert T\rvert$	$\lvert J\rvert \times \lvert C\rvert \times \lvert T\rvert \times \lvert N\rvert$
BigM	$\lvert T\rvert \times (\lvert R\rvert \times \lvert S\rvert \times \lvert I\rvert + (\lvert J\rvert \times \lvert I\rvert \times \lvert K\rvert)^2 + \lvert J\rvert \times \lvert K\rvert \times \lvert C\rvert \times \lvert T\rvert)$	$\lvert N\rvert \times \lvert T\rvert \times (\lvert R\rvert \times \lvert S\rvert \times \lvert I\rvert + (\lvert J\rvert \times \lvert I\rvert \times \lvert K\rvert)^2 + \lvert J\rvert \times \lvert K\rvert \times \lvert C\rvert \times \lvert T\rvert)$

CHAPTER V

COMPUTATIONAL RESULTS

This chapter presents the findings and analysis acquired from the application of the developed models and simulation methodology to real-world scenarios, providing valuable insights into the effectiveness and practical implications of the proposed strategies for managing disruptions in global supply chain networks.

5.1 Problem Configuration

In our computational experiments, two distinct supply chain networks are considered. Table 6 provides an overview of the structures of two different supply chain networks, characterized by the number of suppliers, production facilities, distribution centers, and customers in each network. The visual representation of these supply chain networks can be found in Figure 2 , providing a clear illustration of their respective configurations.

Table 6: Network Structures

Num. of Suppliers	Num. of Production Fac.	Num. of DCs	Num. of Customers
1	2	2	3
2	2	2	2

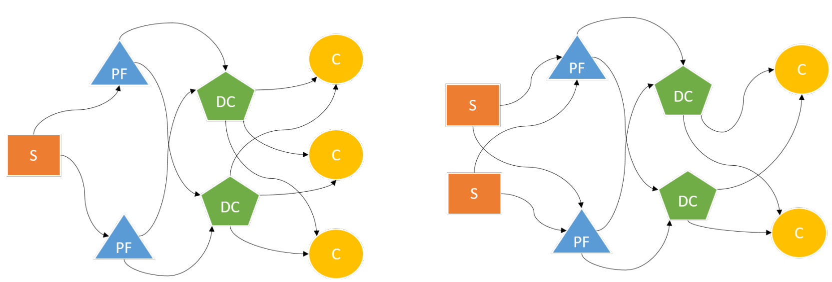

Figure 2: Representation of Supply Chain Networks

The first network comprises one supplier, two production facilities, two distribution centers, and three customers. The second network consists of two suppliers, two production facilities, two distribution centers, and two customers. To ensure a meaningful comparison between the two models after their application and the utilization of results in the simulation method, we maintain the same sizes of the networks in both models. Additionally, the specified assumptions for the analysis are as follows:

- Initial inventory amount of raw material and product type are taken as 0 for both production facilities and distribution centers.
- The value for the consumption amount of the product type is set to 1 unit.
- Backorders are allowed until the end of the specified time horizon.

As an optimization tool, the computational experiments were performed using the JAVA programming language and the Gurobi 9.5 solver on HP Probook 430 G7 laptop with Intel(R) Core(TM) i7 processor running at 1.80 GHz and with 16 GB RAM. The Gurobi solver is capable of finding proven optimal solution for all examples of MILP models with CPU time.

Table 7 presents the structures of two distinct supply chain networks, along with the characteristics of their deterministic and stochastic models. The table showcases key parameters that define the complexity of each network model.

Table 7: Size of MILP Models for the Networks

Networks	MM1			MM2			
	Continuous	Binary	CPU (sec)	Continuous	Binary	CPU (sec)	Scenarios
Network 1	164	48	2.914	1,076,004	48	116.218	6,561
Network 2	136	48	4.531	892,296	48	102.791	6,561

Following the establishment of the network structures, and in preparation for the application of the solution methods of mathematical models and the simulation, we proceeded to generate the required data and scenarios. The purpose is comparing the cost performance of the outcomes obtained from the mathematical models and assess their effectiveness. The details of this data generation process are outlined in the subsequent section.

5.2 Data and Scenario Generation

A methodical approach was employed to generate the essential data required for the analysis. The process of generating data involved randomly generating costs within specified ranges, as presented in Table 8 and Table 9, using insights obtained from relevant literature, [14], [10], [6].

Table 8: Cost Parameters 1

Fixed Cost Prod.			Fixed Cost DC		
OC	O	C	PL	OP	CL
(20000,25000)	(20000,25000)	(20000,25000)	(20000,23000)	(20000,23000)	(20000,23000)

Table 9: Cost Parameters 2

p	b	g	h	pd	pr	sr	sc	sp
(1000,2000)	(250,500)	(2,5)	(2,5)	(2,5)	(2,5)	(1,2)	(1,3)	(1,4)

In this thesis, our objective is to model the real-world interplay between supply and demand under the influence of disruptions, the scenario cases are illustrated in Figure 3. Capacity scenarios are grouped into three categories: "ZERO" capacity, which signifies a complete breakdown of the facility; "HALF" capacity, indicating reduced production or inventory due to disruption effects; and "FULL" capacity, representing an undamaged facility case. Similarly, customer demand scenarios are classified based on the impact of disruptions. "HIGH" demand represents urgent needs of certain products, "MEDIUM" demand represents the level of unaffected product requirements, and "LOW" demand refers to a reduction in product requirements resulting from the prioritization of more critical needs in disaster environments. To achieve these types of cases, we utilized some distribution techniques for generating capacity and demand data. This approach allowed us to model and analyze various disruption cases effectively. These various types of disruptions, affecting both demand and capacities of different facility types, lead to a significant increase in scenario probabilities.

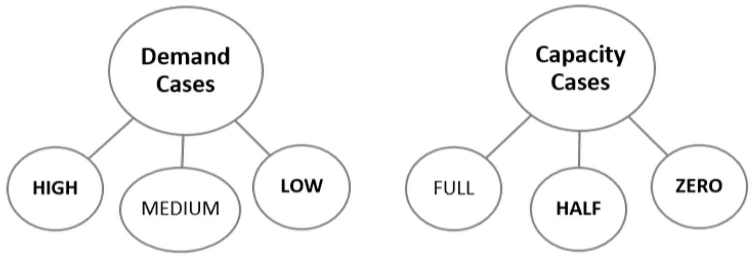

Figure 3: Demand and Capacity Scenarios

During the capacity generation phase of the facilities, a uniform distribution is employed. This approach ensured that the generated capacity values diversified a wide range and accurately represented the potential variations observed in real-world supply chain networks. We have established the probabilities of different disruption cases for each facility, represented in Table 10.

Table 10: Probabilities of Capacity Cases for Each Type of Facilities

Facility Type	Capacity Cases		
	ZERO Capacity	HALF Capacity	FULL Capacity
Suppliers	0.3	0.2	0.5
Production Facilities	0.1	0.3	0.6
Distribution Centers	0.1	0.2	0.7

In addition to the MILP approaches, for generating demand data, we employed a triangular distribution, a commonly used probability distribution in statistics and data analysis. Also, it is suitable to represent our demand scenarios by considering three cases. The triangular distribution is defined by three parameters: the minimum value, maximum value, and mode, which represents the most likely value.

Our demand generation approach involved segmenting the triangular distribution into three distinct areas to represent low, medium, and high demand probabilities. This allowed us to carefully select the parameters of the triangular distribution to match our specific requirements. To create the desired three areas in shaping the probabilities of low, medium, and high demand scenarios, we placed two break points, denoted as k1 and k2, as summarized in Table 11.

Table 11: Triangular Distribution Parameters for Demand Generation

Parameter	**Value**
Minimum Value	4000
Mode (Most Likely Value)	8500
Maximum Value	12000
Breakpoint 1 (k1)	5000
Breakpoint 2 (k2)	9500

Using the provided parameters, we visualize the triangular distribution, as shown in Figure 4. We then calculate the areas corresponding to the demand probabilities, represented as p_{low}, p_{medium}, and p_{high}, as illustrated in Table 12. Furthermore, we determine the expected values for each demand case by computing the integrals within their respective ranges based on the given probability density functions (pdfs) and calculating the corresponding areas.

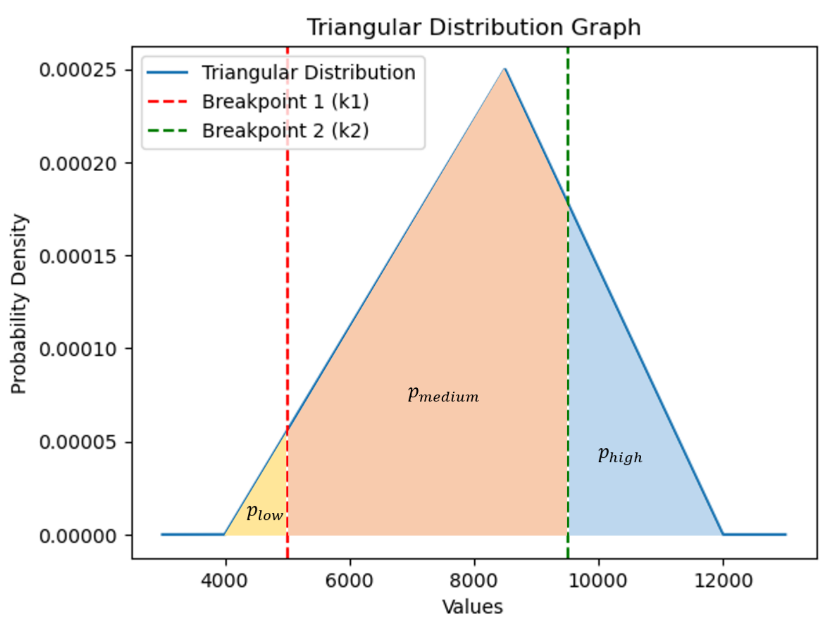

Figure 4: Triangular (4000, 12000, 8500)

Table 12: Demand Probabilities

Demand Cases	Probability
Low (p_{low})	0.081
Medium (p_{medium})	0.747
High (p_{high})	0.174

This segmentation allows us to simulate and analyze different demand patterns effectively, enabling us to study the implications of varying demand levels on our system or process. Moreover, triangular distribution takes the shape of a triangle with a peak at the mode and decreases linearly towards the minimum and maximum values. It is commonly used in scenarios where limited data or expert knowledge is available. Its flexibility makes it suitable for modeling uncertain variables or generating input scenarios for simulation studies. In this thesis, using the triangular distribution for demand data generation can allow you to simulate various demand patterns, aiding in the analysis of their impacts on your system or process. We choose the parameter values to reflect the real-world scenarios for the demand and capacity data. To sum up, by integrating the triangular distribution, the demand values were generated in a manner that reflected the asymmetric nature of disruptions and the likelihood of extreme demand fluctuations.

These variety of demand and capacity cases enable the simulation scenarios to accurately represent the difficulties and uncertainties met by supply chain managers, thereby facilitating some analysis of the proposed strategies and their effectiveness in mitigating disruption impacts. The random generation of data and scenarios ensured the representation of diverse and realistic conditions, allowing for an evaluation of the proposed strategies and solutions. To represent the capacity and demand relationship within specific ranges, random case instances were generated. The generated data for the two networks under consideration can be found in Table 13 and Table 14. In these tables, the ranges of numbers highlighted in bold represent the bottlenecks of each case, implying their significant impact on limiting the distribution of raw materials and products throughout the entire network. The ranges are determined by considering the number of facilities and their total capacities for each echelon, which are based on the constant demand specified. Furthermore, the case values were established with respect to demand using the scenario of MEDIUM demand, while capacities were determined based on the situation of FULL capacity cases, assuming these values in a scenario without any disruptions. In both networks, we maintain a constant customer demand while varying the capacities of the facilities across all cases. This approach allows us to gain a clearer understanding of the relationship between network capacity and demand.

Table 13: Parameter Table for Network 1

Network 1			Supp. Capacity		Prod. Fac. Capacity		DC Capacity		Customer Demand
Case Number	Type of Cases	Num. of Instances	min	max	min	max	min	max	Expected Value
1	s<3c<2dc<2pf	10	**15000**	**35400**	22000	27000	17700	22000	11806.548
2	2pf<3c<s<2dc	10	35420	45000	**7500**	**17700**	22500	25000	11806.548
3	2dc<3c<2pf<s	10	44000	50000	17700	22000	**7500**	**17700**	11806.548
4	3c<2dc<2pf<s	10	54000	60000	22000	27000	17700	22000	**11806.548**

Table 13 presents the data generated for the first network, comprising four randomly generated cases, with ten instances for each case, representing capacity and demand data. Across all cases, various combinations of capacity and demand are explored. For example, in the first case, the conditions s<3c<2dc<2pf indicate that the supplier capacity is lower than the total demand of three customers, and the total demand of three customers is lower than the combined capacity of two distribution centers, which, in turn, is lower than the total capacity of two production facilities. In the second case, the conditions 2pf<3c<s<2dc portray a different scenario. Here, the total capacity of two production facilities is low to meet the total demand of three customers. Additionally, the total demand of three customers is below the supplier's capacity, which in turn is lower than the combined capacity of two distribution centers. Continuing with the third case, we observe the conditions 2dc<3c<2pf<s. In this instance, the combined capacity of two distribution centers falls short of meeting the total demand of three customers, and the total capacity of two production

facilities is lesser than the supplier's capacity. Moving on to the fourth case, we encounter the conditions 3c<2dc<2pf<s. Here, the total demand of three customers is less than the combined capacity of two distribution centers, and the total capacity of two production facilities is less than the supplier's capacity.

These four cases represent a diverse array of scenarios, illustrating different capacity and demand relationships within the first network. By systematically exploring these variations, our analysis aims to offer comprehensive insights into the intricate dynamics between network capacity and demand, thereby informing optimal supply chain operations and decision-making processes.

Table 14: Parameter Table for Network 2

Network 2			Supp. Capacity		Prod. Fac. Capacity		DC Capacity		Customer Demand
Case Number	Type of Cases	Num. of Instances	min	max	min	max	min	max	Expected Value
1	2s<2c<2dc<2pf	10	**7000**	**16808**	16808	21808	11807	16807	11806.548
2	2pf<2c<2s<2dc	10	11807	16807	**7000**	**11806**	16808	21808	11806.548
3	2dc<2c<2pf<2s	10	16808	21808	11807	16807	**7000**	**11806**	11806.548
4	2c<2dc<2pf<2s	10	21809	26809	16808	21808	11807	16807	**11806.548**

In Table 14, data for the second network is presented with comprising again four randomly generated cases, each with ten instances, representing capacity and demand information. These cases illustrate various combinations of capacities and demands based on the second network's size. For instance, in Case 1, the total capacity of two suppliers are lower than the total demand of two customers, which, in turn, is lower than the combined capacity of two distribution centers, and finally, the distribution centers' capacity is lower than the total capacity of two production facilities. Similarly, Case 2 shows a different arrangement of capacities and demands, where the total capacity of two production facilities' capacity are lower than the total demand of two customers, and the total demand of two customers are lesser than the total capacity of two distribution centers. These cases try to represent the network's dynamics under diverse scenarios, providing clarity on the relationship between capacity levels and customer demands, and offering valuable understanding into its performance under different circumstances.

5.3 Simulation Method

To manage a comparative cost analysis of strategic binary decisions, which are open, operate and close decisions, under deterministic (MM1) and stochastic models (MM2), we applied a simulation method. Within our simulation methodology, key strategic decisions such as operating, opening, and closing are considered are treated as binary inputs to enable a cost-performance comparison of these decisions, represented in Figure 5. These decisions are derived from deterministic (MM1) and stochastic models (MM2) to assess the overall costs incurred when faced with diverse disruption scenarios. In other words, this method enables us to value the cost-effectiveness of various decision alternatives when faced with diverse uncertainties and disruptions that commonly appear in real-world supply chain environments.

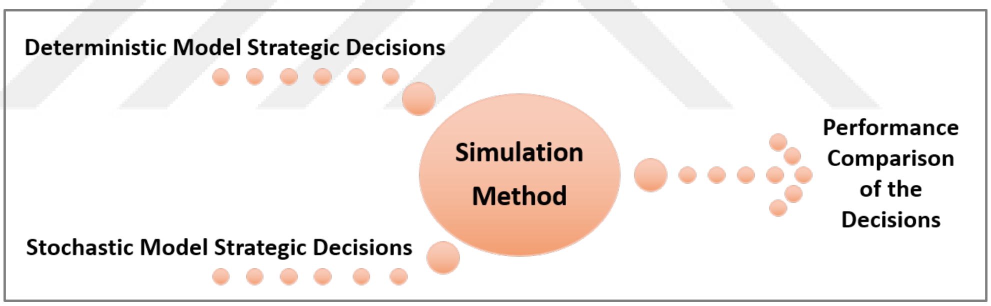

Figure 5: Representation of Simulation Method

The steps of the simulation algorithm explained in Algorithm 1 in detail. By simulating different disruption scenarios, we aim to gain valuable insights into optimal decisions that mitigate the impact of disruptive events and address challenges encountered by companies in their supply chains. These challenges include facility failures and demand volatility, and we take into account different types of costs associated with managing them.

We limited the simulation runs to 30 because we observed that each type of costs were converging for both networks. As an example, total costs convergences of Network 1 for Case 1 are illustrated in Figure 6 with using both deterministic and

Algorithm 1 Simulation Algorithm

Step 1: Set the number of simulation runs as 30.
Step 2: In each run, generate random numbers for the capacity cases of suppliers, production facilities and distribution centers as FULL, HALF, ZERO and for the demand cases of customers as HIGH, MEDIUM, LOW.
Step 3: Solve Mathematical Model 3 (MM3) with the strategic decisions, operate, open and close from both models separately.
Step 4: Calculate all types of costs for each run.
Step 5: Continue steps until the number of simulation runs are completed.

stochastic model. When analyzing the mean of each cost type as we increased the number of runs, we noticed consistently similar outcomes. This similarity in results prompted us to confine the simulation runs at 30.

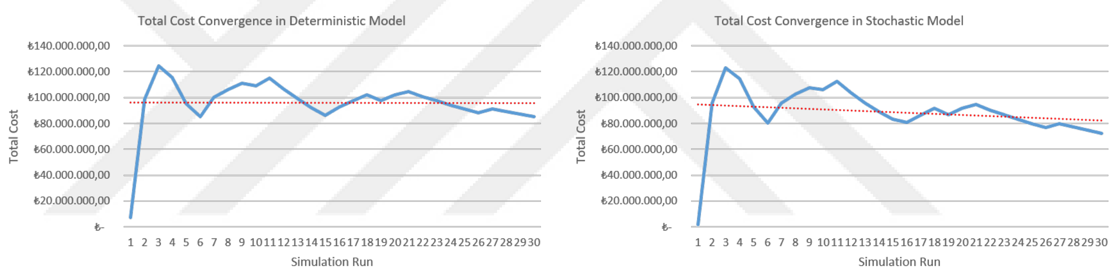

Figure 6: Total Cost Convergences in MM1 and MM2 for Network 1

5.3.1 Mathematical Model for Simulation

This linear programming model (MM3) takes the strategic decisions derived from deterministic and stochastic models as its inputs. Its primary purpose is to assess these decisions in light of multiple cost objectives. In other words, it evaluates the strategic choices considering various cost types to arrive efficient outcomes. Table 15 outlines the sets, parameters, and decision variables of the mathematical model (MM3) used in simulation.

In contrast to the previous models, this particular model does not involve fixed costs for operating, opening, or closing production facilities or distribution centers. That's why this model (MM3) is formulated as a Linear Programming (LP) model.

Table 15: Nomenclature for Math. Model for Sim. (MM3)

Sets	
S	Set of suppliers – s indexed by s
I	Set of production facilities – i indexed by i
K	Set of distribution centers – k indexed by k
C	Set of customer locations – c indexed by c
T	Set of time periods – t indexed by t
J	Set of product types – j indexed by j
R	Set of raw materials – r indexed by r
Parameters	
pr_{rs}	Unit procurement cost of raw material r from supplier s to production facility
pd_{ji}	Unit production cost of product type j in production facility i
g_{jik}	Unit transportation cost of product type j from production facility i to DC k
h_{jkc}	Unit transportation cost of product type j from DC k to customer location c
sc_{ji}	Unit storage cost of product type j in production facility i
sr_{ri}	Unit storage cost of raw material r in production facility i
sp_{jk}	Unit storage cost of product type j in DC k
p_{jc}	Unit penalty cost of unsatisfied demand of product type j in customer location c
b_{jc}	Unit backorder cost of product type j in customer location c
bc_{jc}	Backorder time amount of product type j in customer location c
$caps_{srt}$	Capacity of supplier s for raw material r at period t
cap_{ijt}	Capacity of production facility i for product type j at period t
$capd_{kjt}$	Capacity of each DC k for product type j at period t
d_{cjt}	Demand of customer location c for product type j at period t
F_{it}	1, if production facility i is operated at period t, 0 otherwise
FO_{it}	1, if an inactive production facility i is opened at period t, 0 otherwise
FC_{it}	1, if an active production facility i is closed at period t, 0 otherwise
L_{kt}	1, if DC k is operated at period t, 0 otherwise
LO_{kt}	1, if an inactive DC k is opened at period t, 0 otherwise
LC_{kt}	1, if an active DC k is operated at period t, 0 otherwise
IR_{ri0}	Initial inventory amount of raw material r in production facility i
I_{ji0}	Initial inventory amount of product type j in production facility i
ID_{jk0}	Initial inventory amount of product type j in DC k
β_{ji}	Capacity consumption amount of product type j of production facility i
α_{rj}	Amount of raw material r needed to produce one product type j
M	Arbitrarily large constant
Decision variables	
X_{rsit}	Amount of raw material r procured from supplier s for production facility i at period t
Y_{jit}	Amount of product type j produced by production facility i at period t
Z_{jikt}	Amount of product type j transferred from production facility i to DC k at period t
$D_{jkctt'}$	Amount of product type j distributed from DC k to customer location c in period t' to satisfy demand at period t
I_{jit}	Amount of inventory level of product type j in production facility i at the end of period t
IR_{rit}	Amount of inventory level of raw material r in production facility i at the end of period t
ID_{jkt}	Amount of inventory level of product type j in DC k at the end of period t
LS_{jct}	Amount of penalty for product type j in customer location c at period t

Instead, these strategic decisions, namely, operating, opening, and closing decisions, are now provided as parameters, serving as inputs to the model.

The primary goal of this model is to identify the most cost-efficient strategic decisions, which have been obtained from the deterministic (MM1) and stochastic (MM2) models, by taking into account other decision variables and their associated cost components. To achieve this, the model's objective function and constraints are formulated based on the specified costs and other relevant parameters.

$$\min \sum_{j,c,t} p_{jc} LS_{jct} + \sum_{j,k,c,t}\sum_{t'>t} b_{jc} D_{jkctt'} + \sum_{r,s,i,t} pr_{rs} X_{rsit} + \sum_{j,i,t} pd_{ji} Y_{jit} + \sum_{j,i,k,t} g_{jik} Z_{jikt} + \sum_{j,k,c,t}\sum_{t\leq t'} h_{jkc} D_{jkctt'} + \sum_{j,i,t} sc_{ji} I_{jit} + \sum_{j,k,t} sp_{jk} ID_{jkt} + \sum_{r,i,t} sr_{ri} IR_{rit} \tag{63}$$

$$\text{s.t.} \quad \sum_{i} X_{rsit} \leq caps_{srt} \qquad \forall s \in \mathcal{S}, \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \tag{64}$$

$$IR_{ri0} + \sum_{s} X_{rsit} = \sum_{j} \alpha_{rj} Y_{jit} + IR_{rit} \qquad \forall r \in \mathcal{R}, \forall i \in \mathcal{I}, t = 1 \tag{65}$$

$$IR_{ri(t-1)} + \sum_{s} X_{rsit} = \sum_{j} \alpha_{rj} Y_{jit} + IR_{rit} \qquad \forall r \in \mathcal{R}, \forall i \in \mathcal{I}, t > 1 \tag{66}$$

$$I_{ji0} + Y_{jit} = \sum_{k} Z_{jikt} + I_{jit} \qquad \forall j \in \mathcal{J}, \forall i \in \mathcal{I}, t = 1 \tag{67}$$

$$I_{ji(t-1)} + Y_{jit} = \sum_{k} Z_{jikt} + I_{jit} \qquad \forall i \in \mathcal{I}, \forall j \in \mathcal{J}, t > 1 \tag{68}$$

$$\beta_{ji} Y_{jit} \leq cap_{ijt} * F_{it} \qquad \forall i \in \mathcal{I}, \forall j \in \mathcal{J}, \forall t \in \mathcal{T} \tag{69}$$

$$ID_{jk0} + \sum_{i} Z_{jikt} = \sum_{c} D_{jkctt'} + ID_{jkt} \qquad \forall j \in \mathcal{J}, \forall k \in \mathcal{K}, t = 1 \tag{70}$$

$$ID_{jk(t-1)} + \sum_{i} Z_{jikt} = \sum_{c}\sum_{\tau\leq t} D_{jkc\tau tn} + ID_{jkt} \qquad \forall j \in \mathcal{J}, \forall k \in \mathcal{K}, t > 1 \tag{71}$$

$$ID_{jkt} \leq capd_{kjt} \qquad \forall j \in \mathcal{J}, \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \tag{72}$$

$$\sum_{k} \sum_{t'=t}^{t+bc_{jc}} D_{jkctt'} + LS_{jct} = d_{cjt} \qquad \forall j \in \mathcal{J}, \forall c \in \mathcal{C}, \forall t \in \mathcal{T} \tag{73}$$

$$X_{rsit} \leq M * F_{it} \qquad \forall r \in \mathcal{R}, \forall s \in \mathcal{S}, \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \tag{74}$$

$$Z_{jikt} \leq M * F_{it} \qquad \forall j \in \mathcal{J}, \forall i \in \mathcal{I}, \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \tag{75}$$

$$D_{jkctt'} \leq M * L_{kt} \qquad \forall j \in \mathcal{J}, \forall k \in \mathcal{K}, \forall c \in \mathcal{C}, \forall t \in \mathcal{T}, \forall t' \in \mathcal{T} \tag{76}$$

$$Z_{jikt} \leq M * L_{kt} \qquad \forall j \in \mathcal{J}, \forall i \in \mathcal{I}, \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \tag{77}$$

$$X_{rsit} \geq 0 \qquad \forall r \in \mathcal{R}, \forall s \in \mathcal{S}, \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \tag{78}$$

$$Y_{jit} \geq 0 \qquad \forall j \in \mathcal{J}, \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \tag{79}$$

$$Z_{jikt} \geq 0 \qquad \forall j \in \mathcal{J}, \forall i \in \mathcal{I}, \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \tag{80}$$

$$D_{jkctt'} \geq 0 \qquad \forall j \in \mathcal{J}, \forall k \in \mathcal{K}, \forall c \in \mathcal{C}, \forall t \in \mathcal{T}, \forall t' \in \mathcal{T} \quad (81)$$

$$IR_{rit} \geq 0 \qquad \forall r \in \mathcal{R}, \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \quad (82)$$

$$I_{jit} \geq 0 \qquad \forall j \in \mathcal{J}, \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \quad (83)$$

$$ID_{jkt} \geq 0 \qquad \forall j \in \mathcal{J}, \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \quad (84)$$

$$LS_{jct} \geq 0 \qquad \forall j \in \mathcal{J}, \forall c \in \mathcal{C}, \forall t \in \mathcal{T} \quad (85)$$

The objective function (63) minimizes the total cost by considering penalties, backorders, procurement, production, transportation, storage, operating, opening, and closing costs. Constraints (64) ensure that the total procurement of raw materials from all suppliers for each production facility in each period $t \in T$ does not exceed the suppliers' capacity. Constraints (65) and (66) represent the inventory balance between procurement and production in the production facilities. Constraints (67) and (68) represent the inventory balance between the production facilities and the distribution centers (DCs). Constraints (69) indicate capacity constraints on each production facility. Constraints (70) and (71) represent the flow balance between the DCs and the customers. Constraints (72) ensure that the inventory level in the DCs does not exceed their capacity. Constraints (73) guarantee that customer demand is satisfied. Constraints (74) and (75) are Big-M constraints that allow a production facility to produce and send a specific amount if it is decided to be operated. Constraints (76) and (77) are Big-M constraints that enable a DC to procure and send a specific amount if it is decided to be operated. Since we already know the decisions for cases where F and L are zero, we can eliminate X, Y, Z and D decision variables from the beginning and omit these constraints accordingly. Finally, constraints (78), (79), (80), (81), (82), (83), (84) and (85) are non-negativity constraints.

5.3.2 Hypothesis Testing

After completing the simulation, we aim to prove that the expected cost of the stochastic model is lower than the cost of deterministic model, when the models face with the real life disruption scenarios. Then we developed our hypothesis according to this state to determine if the total cost of the stochastic model is lower, and hence, we formulated the hypothesis H_1 to support this notion. We used left-tailed hypothesis testing approach, as shown in Figure 7, to evaluate our hypothesis.

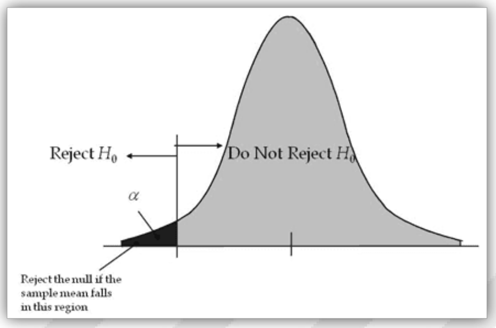

Figure 7: Left-tailed Hypothesis Testing

Since, in a left-tailed test, the alternative hypothesis H_1 states that the parameter of interest is less than a specified value, that matches with our main focus. According to left-tailed hypothesis testing, rejection region is on the left side of the distribution. If we reject the null hypothesis H_0, it would indicate that the stochastic model indeed produces better outcomes. Thus, the null hypothesis H_0 asserted that the total cost of the stochastic model is greater than or equal to that of the deterministic model. Conversely, the alternative hypothesis H_1 stated that the total cost of the stochastic model is lower than that of the deterministic model, represented as follows:

Null hypothesis:

$$H_0 : \mu_{\text{stochastic}} \geq \mu_{\text{deterministic}}$$

Alternative hypothesis:

$$H_1 : \mu_{\text{stochastic}} < \mu_{\text{deterministic}}$$

To perform and evaluate hypothesis testing for the cost comparison results, obtained from the simulation of the deterministic and stochastic models' decisions, we determined necessary parameters. In this test, we used significance level as 0.05, means that there is a 5% chance of making a Type I error. Lower significance levels (e.g., 0.01) provide higher confidence but may increase the risk of Type II errors (failing to reject the null hypothesis when it is false), which is why 0.05 is often used as a compromise in many fields. We collected a sample size of 300 for each cost type in both networks, considering all cases. Due to the large number of instances, we performed a z-test to analyze the test statistics. The zStat was computed as the difference between the total of stochastic and deterministic costs, divided by the standard error, for each cost type in each case. We then determined the critical value (p-value) from the standard normal distribution based on the chosen zStat. Subsequently, we made conclusions based on whether the absolute value of the calculated z-statistic was less than the z-critical value (i.e., $zStat < z_{\text{critical}}$), in which case we rejected the null hypothesis. Otherwise, if the absolute value of the calculated z-statistic was greater than or equal to the z-critical value, we failed to reject the null hypothesis.

5.3.3 Comparison Results

This section presents a detailed analysis of the cost comparisons between deterministic and stochastic models for both models. After simulating the results of their respective decisions, we conducted hypothesis testing to determine whether the costs of the stochastic model are lower than those of the deterministic model for various types of costs. In the first network, we have 1 supplier, 2 production facilities, 2 distribution centers, and 3 customers. In the second network, there are 2 suppliers, 2 production facilities, 2 distribution centers, and 2 customers. For both networks, we conducted a thorough examination of various types of cost comparisons, including total costs, penalty, procurement, production and total transportation costs. Hence, comparing the models based on these costs metrics would provide a good evaluation.

The following Table 16, Table 17, Table 18, Table 19, Table 20 represent the cost analysis of the first network, considering various cost categories, including total costs, penalties, procurement expenses, production costs and total transportation costs.

Table 16: Network 1 - Total Cost Comparison

Case Number	Type of Cases	Z-value	p-value	Reject or Fail to Reject
1	s<3c<2dc<2pf	-3.11	0.000937	Reject H_0
2	2pf<3c<s<2dc	-0.45	0.325657	Fail to Reject H_0
3	2dc<3c<2pf<s	-3.92	0.000045	Reject H_0
4	3c<2dc<2pf<s	-1.05	0.145957	Fail to Reject H_0

Regarding our hypothesis statement H_1, Table 16 shows the results of hypothesis testing, and based on the given information, we can see that for Case 1 and Case 3, the p-values are less than the significance level ($0.000937 < 0.05$ and $0.000045 < 0.05$, respectively). Therefore, we reject the null hypothesis H_0 in both of these cases, indicating that there is a significant difference between the costs of stochastic and deterministic models. In other words, the data provides evidence to support the alternative hypothesis H_1, which suggests that there is sufficient evidence to conclude that the total cost of the stochastic model is lower than the total cost of the deterministic model. Based on the hypothesis testing results companies should consider employing stochastic models as they have been found to be significantly more cost-efficient than deterministic models, which aligns with our main objective of minimizing total costs.

For Case 2 and Case 4, the p-values are greater than the significance level ($0.325657 \geq 0.05$ and $0.145957 \geq 0.05$, respectively). Therefore, in both of these cases, we fail to reject the null hypothesis H_0, indicating that there is no significant difference between the costs of stochastic and deterministic models. The data does not provide enough evidence to support the alternative hypothesis H_1 for these cases. Based on these results, in cases where the null hypothesis is not rejected (i.e., Case 2 and Case 4), there is no enough evidence to conclude that the total cost of the stochastic model is lower than the total cost of the deterministic model.

From the table 17, we can again see that for Case 1 and Case 3, the p-values are less

Table 17: Network 1 - Penalty Cost Comparison

Case Number	Type of Cases	Z-value	p-value	Reject or Fail to Reject
1	s<3c<2dc<2pf	-3.09	0.001016	Reject H_0
2	2pf<3c<s<2dc	-0.45	0.325423	Fail to Reject H_0
3	2dc<3c<2pf<s	-3.94	0.000040	Reject H_0
4	3c<2dc<2pf<s	-1.05	0.145856	Fail to Reject H_0

than the significance level $(0.001016 < 0.05)$ and $(0.000040 < 0.05)$, respectively. As a result, we reject the null hypothesis H_0 in both of these cases, indicating that there is a significant difference between the costs of stochastic and deterministic models. This means that the data provides evidence to support the alternative hypothesis H_1.

Conversely, for Case 2 and Case 4, the p-values are greater than the significance level $(0.325423 \geq 0.05)$ and $(0.145856 \geq 0.05)$, respectively. As a result, in both of these cases, we fail to reject the null hypothesis H_0, suggesting that using deterministic model is sufficient enough in terms of cost efficiency. Thus, the data does not provide enough evidence to support the alternative hypothesis H_1 for these cases.

Based on the results presented in the table 17, companies should consider utilizing stochastic models when facing scenarios where the null hypothesis is rejected (i.e., Case 1 and Case 3) since these models have been found to be significantly more cost-efficient than deterministic models concerning the "Penalty Cost" criterion. In situations where Case 2 and Case 4 occur, companies do not need to generate stochastic models. Instead, they can directly utilize deterministic models with their respective expected values.

Table 18: Network 1 - Procurement Cost Comparison

Case Number	Type of Cases	Z-value	p-value	Reject or Fail to Reject
1	s<3c<2dc<2pf	3.39	0.999651	Fail to Reject H_0
2	2pf<3c<s<2dc	0.50	0.690604	Fail to Reject H_0
3	2dc<3c<2pf<s	4.37	0.999994	Fail to Reject H_0
4	3c<2dc<2pf<s	1.15	0.875940	Fail to Reject H_0

From the table 18, we can observe that for all the cases (Case 1, Case 2, Case

3, and Case 4), the p-values are greater than the significance level ($0.999651 \geq 0.05$, $0.690604 \geq 0.05$, $0.999994 \geq 0.05$, and $0.875940 \geq 0.05$, respectively). Consequently, in each of these instances, we do not find enough evidence to reject the null hypothesis H_0. This implies that the cost disparity between stochastic and deterministic models is negligible when considering the "Procurement Cost" criterion. Businesses can therefore choose to persist with deterministic models for estimating procurement costs, as there is no noteworthy cost efficiency advantage favoring stochastic models in these specific cases.

Table 19: Network 1 - Production Cost Comparison

Case Number	Type of Cases	Z-value	p-value	Reject or Fail to Reject
1	s<3c<2dc<2pf	4.24	0.999989	Fail to Reject H_0
2	2pf<3c<s<2dc	0.48	0.684914	Fail to Reject H_0
3	2dc<3c<2pf<s	3.10	0.999030	Fail to Reject H_0
4	3c<2dc<2pf<s	0.02	0.507694	Fail to Reject H_0

Similar findings were observed when applying hypothesis testing based on the "Production Cost" criterion as in the case of the "Procurement Cost" criterion which is shown in Table 19. The results indicate that there is no significant difference between the costs of stochastic and deterministic models for the scenarios considered (Case 1, Case 2, Case 3, and Case 4). Consequently, companies may not find a compelling advantage in favor of stochastic models over deterministic models concerning the "Production Cost" aspect. As a result, the decision to use either type of model should take into account other relevant factors and considerations.

Table 20: Network 1 - Total Transportation Cost Comparison

Case Number	Type of Cases	Z-value	p-value	Reject or Fail to Reject
1	s<3c<2dc<2pf	3.16	0.999214	Fail to Reject H_0
2	2pf<3c<s<2dc	0.51	0.695244	Fail to Reject H_0
3	2dc<3c<2pf<s	4.78	0.999999	Fail to Reject H_0
4	3c<2dc<2pf<s	1.46	0.927688	Fail to Reject H_0

Table 20 presents the comparison results for Network 1 in terms of total transportation cost for four different cases of capacities and demands. In all four cases, the Z-values are less than their respective critical values, leading us to fail to reject the null hypothesis. This implies that there is also no statistically significant difference in total transportation cost between the stochastic and deterministic models in the given scenarios.

To summarize, the computational results from first network scenarios have led to several significant conclusions that hold implications for supply chain companies. Firstly, when both Case 2 and Case 4 occur and the Fail to Reject result consistently aligns across all cost types, the direct employment of a deterministic model emerges as a favorable strategy. On the other hand, when dealing with Case 1 or Case 3 scenarios where total cost or penalty cost is crucial, a stochastic model can significantly enhance cost-effectiveness. Nonetheless, deterministic models are suitable for handling procurement, production, and total transportation costs for these cases. This finding eliminates the need for complex stochastic models, offering substantial advantages in terms of time and computational resource savings. The consistency between stochastic and deterministic model outcomes indicates that the deterministic model yields reliable predictions, thereby facilitating confident decision-making for companies. As these cost elements often exhibit less sensitivity to randomness and uncertainty, the deterministic model proves to be an efficient and practical choice for handling these crucial aspects of supply chain management.

The subsequent tables, namely Table 21, Table 22, Table 23, Table 24, Table 25 present a comprehensive cost analysis of the second network. These tables contain diverse cost categories, such as total costs, penalties, procurement, production and total transportation costs.

Table 21: Network 2 - Total Cost Comparison

Case Number	Type of Cases	Z-value	p-value	Reject or Fail to Reject
1	2s<2c<2dc<2pf	-3.55	0.000194	Reject H_0
2	2pf<2c<2s<2dc	-0.01	0.494150	Fail to Reject H_0
3	2dc<2c<2pf<2s	-4.20	0.000014	Reject H_0
4	2c<2dc<2pf<2s	-2.51	0.006087	Reject H_0

Table 21 presents the comparison results for Network 2 in terms of total cost for four different cases of capacities and demands. Each row represents a specific case, and the table provides relevant statistical information to evaluate the significance of the results. By comparing the Z-value with the critical value, we can determine whether to reject or fail to reject the null hypothesis (H_0). For Cases 1, 3, and 4, the Z-values are less than their respective critical values, leading us to reject the null hypothesis. This indicates that there is a statistically significant difference in total cost between the stochastic and deterministic models in these cases. However, for Case 2, the Z-value is greater than the critical value, leading us to fail to reject the null hypothesis. This implies that there is no statistically significant difference in total cost between the two models for Case 2. Therefore, in the occurrence of Cases 1, 3, and 4, the implementation of the stochastic model proves to be cost-efficient. However, if Case 2 arises, and companies prioritize the total cost of the network, then the deterministic model becomes a sufficient choice.

Table 22: Network 2 - Penalty Cost Comparison

Case Number	Type of Cases	Z-value	p-value	Reject or Fail to Reject
1	2s<2c<2dc<2pf	-3.61	0.000156	Reject H_0
2	2pf<2c<2s<2dc	-0.07	0.470681	Fail to Reject H_0
3	2dc<2c<2pf<2s	-4.07	0.000023	Reject H_0
4	2c<2dc<2pf<2s	-2.49	0.006445	Reject H_0

In Table 22, when Cases 1, 3, and 4 occur, the test results show a rejection of the null hypothesis. This indicates that there is a statistically significant difference in penalty cost between the stochastic and deterministic models in these cases. Consequently, the results suggest a preference for the stochastic model due to its better performance in terms of penalty cost in the specified cases. However, for Case 2, the Z-value is greater than the critical value, and this implies that there is no statistically significant difference in penalty cost between the two models for Case 2.

Table 23: Network 2 - Procurement Cost Comparison

Case Number	Type of Cases	Z-value	p-value	Reject or Fail to Reject
1	2s<2c<2dc<2pf	4.64	0.999998	Fail to Reject H_0
2	2pf<2c<2s<2dc	0.10	0.540725	Fail to Reject H_0
3	2dc<2c<2pf<2s	4.48	0.999996	Fail to Reject H_0
4	2c<2dc<2pf<2s	2.56	0.994819	Fail to Reject H_0

In the Table 23, for all four cases, the z-values are less than their respective critical values, leading us to fail to reject the null hypothesis. This implies that there is no statistically significant difference in procurement cost between the stochastic and deterministic models in any of the specified cases. Therefore, from a statistical standpoint, both models perform similarly in terms of procurement cost across different capacities and demands in Network 2. Since there is no statistically significant difference in procurement cost between the stochastic and deterministic models, companies can confidently choose deterministic model for managing procurement operations in Network 2, due to the other factors, such as ease of implementation, data availability, and computational complexity.

Table 24: Network 2 - Production Cost Comparison

Case Number	Type of Cases	Z-value	p-value	Reject or Fail to Reject
1	2s<2c<2dc<2pf	4.99	1.000000	Fail to Reject H_0
2	2pf<2c<2s<2dc	0.02	0.507873	Fail to Reject H_0
3	2dc<2c<2pf<2s	1.98	0.976079	Fail to Reject H_0
4	2c<2dc<2pf<2s	-0.16	0.435886	Fail to Reject H_0

From Table 24, in all four cases, like procurement cost, the z-values are less than their respective critical values, leading us to fail to reject the null hypothesis. This implies that there is no statistically significant difference in production cost between the stochastic and deterministic models in any of the specified cases. Therefore, from a statistical standpoint, both models perform similarly in terms of production cost across different capacities and demands in Network 2. From these results, we can say that, companies can consider incorporating with the deterministic model, although there are production-related uncertainties and fluctuations in demand. Because based on the production cost, stochastic model is not significantly cost-efficient than the deterministic model.

Table 25: Network 2 - Total Transportation Cost Comparison

Case Number	Type of Cases	Z-value	p-value	Reject or Fail to Reject
1	2s<2c<2dc<2pf	4.07	0.999977	Fail to Reject H_0
2	2pf<2c<2s<2dc	0.06	0.524581	Fail to Reject H_0
3	2dc<2c<2pf<2s	4.73	0.999999	Fail to Reject H_0
4	2c<2dc<2pf<2s	3.37	0.999625	Fail to Reject H_0

As the results of the consideration of procurement and production costs, there is no statistically significant difference in total transportation cost between the stochastic and deterministic models in any of the specified cases. Since there is no statistically significant difference in total transportation cost between the stochastic and deterministic models, companies can apply deterministic model with confidence for managing transportation operations in Network 2.

In conclusion, the computational results from both network scenarios provide robust evidence supporting the use of deterministic and stochastic models depending on the specific cost concerns. Companies can confidently employ deterministic model when especially procurement, production, or total transportation costs are the primary considerations. Adopting stochastic model is highly recommended for situations where mostly total cost or penalty cost is a significant factor. The incorporation of uncertainty and variability in these cases can yield cost-efficient outcomes. Overall, these conclusions contribute valuable insights to inform supply chain decision-making, aiding companies in achieving more effective and informed strategies to optimize their supply chain performance.

CHAPTER VI

CONCLUSION

The management of disruptions in global supply chain networks has emerged as a critical aspect of strategic decision-making in today's dynamic business view. We examined the challenges posed by disruptions and has proposed practical strategies for mitigating their impacts. Through a comprehensive literature review, various factors contributing to disruptions, such as natural disasters, geopolitical instability, and pandemics, have been examined. The importance of optimizing supply chain networks while minimizing various costs has been highlighted. Overall, the objective function represents the total cost of the system.

We presented two mathematical models as deterministic and stochastic, combined with a thorough literature review, underlying its role as a decision-support mechanism for supply chain managers. The mathematical model enables the optimization of procurement, production, distribution, and demand satisfaction decisions, taking into account factors such as demand volatility, facility disruptions, and resource allocation. By integrating scenario-based analysis, the stochastic MILP model facilitates the identification of robust and cost-effective solutions to enhance supply chain resilience. As our main contribution to this field, we emphasized the need for proactive disruption planning, considering multiple disruption scenarios over a finite planning horizon.

Simulation results have demonstrated that the proposed mathematical models, both deterministic and stochastic, offer efficient solutions for managing disruptions in the supply chain. The models take into account real-world factors such as demand volatility, facility disruptions, and resource allocation, which allow supply chain managers to make informed decisions that enhance resilience and minimize costs. Through scenario-based analysis, the models have proven capable of identifying optimal strategies for the supply chain over finite planning horizons, thereby supporting proactive disruption planning. The hypothesis testing conducted in this research has allowed for a rigorous assessment of the proposed strategies' effectiveness. The comparison of stochastic and deterministic models' costs based on the total cost, penalty cost, procurement cost, production cost and total transportation cost criteria revealed consistent findings across all cases.

The analysis of the network's results has significant implications for supply chain companies. When cost considerations are the primary focus, adopting a deterministic model proves to be a viable and efficient option for addressing procurement, production, and total transportation costs. This approach regularizes decision-making and offers practical benefits, as these cost elements are generally less influenced by uncertainty. When the main concern lies in total cost or penalty cost, the findings strongly recommend the use of a stochastic model. Accounting for uncertainty and variability in such scenarios can lead to cost-efficient outcomes. However, it is crucial for supply chain companies to approach these conclusions with careful validation in their specific operational context, considering data availability, and conducting thorough cost-benefit analyses to ensure optimal and well-informed decision-making in supply chain management.

In conclusion, after evaluating the supply chain's performance across various disruption scenarios and considering the implementation of the suggested strategies, statistical evidence has demonstrated that these strategies effectively mitigate the adverse consequences of disruptions. This reinforces the notion that adopting proactive mitigation measures can indeed enhance a supply chain's ability to withstand disruptions and maintain its operational efficiency and competitiveness. The findings of this study make a valuable contribution to the current understanding of supply chain management, specifically in relation to addressing multiple disruptions at various echelons of the supply chain. These findings have important implications for supply chain managers as they make an effort to effectively overcome the challenges presented by disruptions.

Moving forward, further research can explore additional dimensions of supply chain disruptions within larger networks and evaluate the effectiveness of different mitigation strategies in real-world settings. Continuous efforts to enhance supply chain resilience will be crucial to enable organizations to adapt to evolving disruptions and maintain their competitive advantage in the global market.

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