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Research Article

Two-Stage Stochastic Programming and Robust Optimization Models for Resilient Supply Chain Network Design under Uncertainty: A Real Case Study

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ABSTRACT

This paper investigates the resilient multi-period, multi-stage supply chain (SC) network design problem under demand and raw material quality uncertainty within a just-in-time (JIT) distribution setting, based on a real case study. The proposed approach models a four-stage SC comprising suppliers, manufacturers, distributors, and retailers, and develops two-stage stochastic programming and robust optimization models to enhance resilience. Unlike existing studies, this research uniquely integrates JIT distribution with the simultaneous consideration of demand and raw material quality uncertainties, providing practical, data-driven insights for decision-makers. Computational results show that the proposed models produce applicable solutions for real-world implementation. Across all models, high-quality raw materials are preferred 54% in the deterministic model, 55% on average in 30 of 40 stochastic scenarios, and 52% in the robust model, even under worst-case conditions. These findings indicate that prioritizing high-quality raw materials, despite higher purchasing costs, is crucial for maintaining JIT principles and ensuring on-time deliveries. Furthermore, the results highlight that the strategic location of distributors is critical to meeting retailers' demand at the right time and in the right quantity.

Keywords: Two-stage stochastic programming, robust optimization, supply chain network design, the uncertainty of demand and raw material quality, just-in-time distribution
2020 Mathematics Subject Classification: 90B06, 90C15, 90C17

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1 Introduction

A supply chain (SC) consists of multiple suppliers, manufacturers, distributors, and customers to maintain operations that begin with raw materials acquired from suppliers and end with final products delivered to customers, hereinafter referred to as retailers [5]. The studies related to the SC design appeared in the early 1980s due to the wide range of industrial application areas. Since then, a lot of interest has been raised by scholars in this field to solve problems from real-world SCs [27].

As a backbone of the circular economy, the SC should be able to operate in an environment in which the parameters change with uncertainty. Because uncertainty has a considerable impact on the SC, a sustainable SC design cannot be achieved by avoiding the uncertainty inherent in the parameters. In this respect, realistic assumptions and parameters influence the decisions made to achieve reliable SC design [24].

Being thus motivated, this study investigates a multi-period, multi-stage resilient SC network design problem considering uncertainties in both demand and raw material quality—factors that, to the best of our knowledge, have not been jointly addressed within a JIT distribution framework. While prior studies have examined these uncertainties separately or without accounting for the strict timing requirements of JIT systems, a clear gap remains in integrated modeling approaches that capture their combined impact on SC design. To fill this gap, we propose two-stage stochastic programming and robust optimization models, applying them to a real case study. In the stochastic programming model, a scenario-based approach is employed to address uncertainties in demand and raw material quality ratios, whereas the robust optimization model conducts a worst-case analysis to ensure solution feasibility under the most adverse scenario [26]. This guarantees that the solutions obtained from the robust model meet the requirements of extreme conditions due to its conservative methodology. However, because robust optimization focuses exclusively on the single worst-case scenario, it may overlook other potentially significant cases. To mitigate this limitation, the two-stage stochastic programming model incorporates multiple scenarios to represent commonly encountered conditions related to demand and raw material quality ratios.

By leveraging these models, this study aims to address key research questions concerning the design and operation of resilient SCs:
- How do demand and raw material quality uncertainties influence strategic decisions such as distributor locations, material sourcing, and delivery timing in a JIT system?
- What is the impact of raw material quality on overall SC performance and cost?
- How do the outcomes of deterministic, stochastic, and robust optimization models compare, and what practical insights can be drawn for real-world implementation?

The major contributions of the paper are highlighted from several aspects as follows:
- From a theoretical perspective, to the best of our knowledge, this study is the first to jointly address uncertainties in both demand and raw material quality within a JIT distribution context for a multi-period, multi-stage SC design problem. By proposing two approaches—two-stage stochastic programming and robust optimization models—it provides a novel methodological framework for designing resilient SCs that explicitly accounts for both typical and extreme operational conditions.
- From a practical perspective, the proposed two-stage stochastic programming and robust optimization models are applied to a real-world case study from the SC of a hazelnut company in Giresun, Türkiye, demonstrating their applicability in practice.
- From a managerial perspective, the analysis reveals significant managerial insights, highlighting key decision points for distributor locations, material sourcing, and delivery scheduling under uncertainty, thereby guiding supply chain managers in implementing JIT-oriented resilient strategies effectively.

The remainder of the paper is structured as follows.

A comprehensive literature review, summarizing relevant studies, is presented in Section 2. The optimization models addressing uncertainty are proposed in Section 3, along with the problem description. Section 4 focuses on the case study and computational analysis, with results provided in the same section. Section 5 discusses the findings and managerial insights derived from the results. Finally, conclusion is presented in Section 6.

2 Literature Review

The SC network design problem has emerged as a prominent research area due to its significant contributions to optimizing facility location decisions, minimizing costs, and enhancing resource allocation efficiency ([16]). Early studies predominantly adopted deterministic approaches, assuming complete certainty in parameters and system behavior ([33], [34]). Although these studies established a foundational understanding of SC optimization, the deterministic assumptions have been increasingly criticized for their inability to capture real-world uncertainties, such as fluctuating demand, variable lead times, and disruptions. Moreover, the growing prevalence of such uncertainties has underscored the importance of adaptability in SC networks, with a particular focus on integrating sustainability and resilience to ensure long-term viability in dynamic environments ([37]). In response, recent research has shifted toward addressing uncertainty through solution methodologies, including stochastic programming, robust optimization, and probabilistic approaches, to enhance resilience and promote sustainable SC operations ([15]). For example, [6] proposed a scenario-based stochastic programming approach to design a multi-product SC network under demand and supply uncertainties. The model incorporates the cut-set concept from reliability theory to address potential route disruptions. They determined the optimal locations for distribution centers considering usable routes, budget limitations, and capacity constraints in a case study from the food industry. [13] devised a two-stage stochastic programming model for disaster-relief SCs under demand uncertainty and arc disruptions. The model defines product flow between nodes while accounting for capacity limitations. Additionally, it evaluates arc survivability, resource vulnerability, and demand estimation by incorporating a finite set of disaster scenarios to address uncertainty and improve SC resilience. [5] formulated a nonlinear stochastic programming model for multi-period SC network design, focusing on warehouse locations under demand and production time uncertainties. The model aimed to minimize the variance of the net present value, thereby enhancing the robustness of the solution. [25] employed a multi-objective robust possibilistic programming approach for designing a sustainable SC network under demand and transportation cost uncertainties. The model aims to optimize the financial, environmental, and social impacts of the SC while determining amount of product flow, selecting the best suppliers, and choosing the appropriate transportation mode. [4] investigated the SC network design problem, focusing on product quality uncertainty in the mining industry. They suggested a two-stage stochastic programming model to manage uncertainty and strengthen SC resilience. The model seeks to maximize total profit by determining optimal facility locations, material flow quantities, and inventory levels. [18] presented a robust, risk-aware, resilient, and sustainable SC network design to address demand fluctuations. A two-stage robust stochastic programming model is formulated to minimize costs, carbon emissions, and energy consumption, while simultaneously maximizing employment. [36] investigated the medical SC network design problem and proposed a hybrid risk management framework to enhance resilience and adaptability. They developed a two-stage stochastic programming model that integrates conditional value at risk (CVaR) and chance constraints to manage the risk of unsatisfied demand. The model determines the optimal warehouse locations and the quantities of products to be transferred by considering capacity uncertainty. These studies emphasize the importance of integrating uncertainty and highlight the need for uncertainty-aware solution methodologies in SC network design. They underscore

the critical role of these approaches in developing resilient, adaptable, and sustainable systems capable of withstanding disruptions and responding to dynamic environments.

Despite these advancements, studies integrating JIT distribution with SC network design problem under uncertainty remain limited. [33] developed a mathematical model for a multi-stage SC network design problem by integrating the JIT delivery policy, where a kanban is associated with a transporter. The model determines the number of kanban, batch size, number of batches, and the total quantity over a given period. To solve the problem, a branch and bound method was utilized. [11] examined a multi-period, multi-product, and multi-stage SC by considering capacities and distribution times. They proposed a mathematical model for JIT distribution, aimed at minimizing earliness and tardiness in deliveries, while determining the optimal location of facilities. To tackle the problem, genetic algorithm was employed. [21] formulated an optimization model for JIT logistics problems within a two-stage SC network. To achieve JIT principles, they introduced constraints on inventory and backorder levels to ensure that products are delivered precisely when needed, without overstocking or stockouts. These studies emphasize that integrating JIT distribution into SC network design enhances operational efficiency by reducing inventory levels, minimizing lead times, and improving responsiveness.

This section provides a comprehensive literature review on SC network design problems, focusing particularly on the role of uncertainties and the JIT distribution perspective. In this context, Table 1 categorizes the related works based on problem specifications, types of uncertainties, and solution methodologies, offering a structured overview of the current state of research in this domain. By systematically analyzing these factors, the literature review reveals a significant gap in the existing research. While numerous studies focus on SC network design under uncertainty, only a limited number examine JIT distribution in this context. Among those addressing JIT distribution within SC network design, none investigate uncertainties related to raw material quality. Motivated by this gap, this paper addresses a multi-stage, multi-period SC network design problem that incorporates JIT distribution under raw material quality and demand uncertainties. Integrating these uncertainties into the SC network design ensures resilience and sustainability while maintaining operational efficiency. Moreover, JIT principles are reinforced by maintaining delivery lead time intervals and preventing inventory accumulation and backorders, thereby enhancing adaptability and responsiveness. To formulate the problem, two advanced optimization models are proposed: a two-stage stochastic programming model and a robust optimization model. The proposed models offer a valuable tool for both practitioners and researchers seeking to design robust, sustainable, and resilient SC capable of performing reliably under uncertain conditions.

3 Problem Formulation through Optimization Models

3.1 Problem Definition

This study investigates a multi-stage, multi-period sustainable and resilient SC network design that integrates JIT distribution while addressing uncertainties in raw material quality and demand. The SC network consists of multiple suppliers (denoted by the set S), providing raw materials with varying quality levels, manufacturing facilities (denoted by the set M), processing these materials into final products, and distribution centers (denoted by the set D), facilitating the delivery of products to retailers (denoted by the set R). The structure of the SC is depicted in Figure 1. The objective is to minimize total SC costs, including the procurement, the transportation, the holding, the facility opening, and the penalty costs, while ensuring resilience, sustainability, and operational efficiency. JIT principles are integrated by maintaining delivery lead time intervals, preventing excess inventory and backorders, and enhancing the adaptability and respon-

Table 1: Summary of the studies regarding SC design under uncertainty

Authors	**Problem Specification**				**Solution Methodology**					
	Period	JIT	Uncertainty	Other	RCS	DO	FP	SP	RO	Other
[34]	Multi	•				•				
[33]	Single	•		•		•				•
[11]	Multi	•								•
[6]	Single		D; DT		•			•		
[13]	Single		ADT			•		•		
[12]	Multi	•				•				•
[20]	Multi	•		•						•
[22]	Multi	•		•						•
[5]	Multi		D; T					•	•	
[21]	Multi	•	D; CT				•			•
[3]	Multi		PQ	•					•	
[28]	Single		LT				•	•		
[25]	Single		D; C	•			•		•	
[32]	Multi		D; DT		•			•		•
[14]	Multi	•				•				
[26]	Single		CT; ADT	•	•	•			•	
[37]	Single		ADT	•	•	•		•		
[10]	Multi		D; RT	•	•		•		•	•
[29]	Multi		D	•	•			•		
[23]	Single		C; D		•		•	•		
[1]	Multi		DT		•			•		•
[4]	Multi		PQ		•	•		•		
[9]	Single		D		•	•				•
[30]	Single		D	•		•				•
[2]	Multi		D	•	•					•
[8]	Single		D	•				•		•
[18]	Multi		D	•	•				•	•
[35]	Single		D; CT	•				•		•
[17]	Single		C	•					•	•
[36]	Single		D; CT					•		•
Present Study	Multi	•	D; RMQ		•	•		•	•	

Notes: JIT = Just-in-Time, RCS = Real Case Study, DO = Deterministic Optimization, FP = Fuzzy Programming, SP = Stochastic Programming, RO = Robust Optimization, D = Demand, DT = Disruption, ADT = Arc Disruption, PQ = Product Quality, C = Cost, T = Time, CT = Capacity, LT = Lead Time, RMQ = Raw Material Quality.

siveness of the SC network. The decision-making process involves determining raw material reprocessing quantities, selecting distribution centers to be opened, and coordinating product flows to retailers as needed over a planning horizon of T periods.

To address uncertainties in demand and raw material quality, the problem is formulated using two-stage stochastic programming and robust optimization models. The stochastic programming model leverages multiple scenarios to represent different realizations of uncertainty, aiming to minimize the expected total cost across all scenarios. In the two-stage stochastic programming model, two types of decision variables are considered to minimize costs: (i) here-and-now decisions (first-stage decisions), which involve long-term commitments -such as the selection of distribution centers- that must be made before uncertainty is realized, and (ii) wait-and-see decisions (second-stage decisions), which represent operational adjustments -such as the quantities of materials and products to be transported, inventory levels, reprocessing activities, and backorder management- that can be made after uncertainty is revealed. This distinction reflects the real-world nature of SC management, where strategic facility investments must be made in advance, while operational decisions can be dynamically adjusted based on updated information. Here-and-now decisions establish the foundational structure of the SC, while wait-and-see decisions offer the flexibility needed to optimize operations based on actual conditions [37].

In contrast, the robust optimization model provides a more conservative approach to uncertainty management by focusing on the worst-case performance [26]. Unlike the two-stage stochastic programming model, robust optimization does not rely on a predefined set of probabilistic scenarios. Instead, it seeks to optimize decisions for the worst-case realization within a specified uncertainty set [25]. This study employs an interval-polyhedral uncertainty set to represent uncertainty in parameters. Compared to traditional interval or box uncertainty sets, this approach provides a more flexible and practical representation of uncertainty. While interval-based uncertainty focuses on capturing the upper and lower bounds of uncertain parameters, the polyhedral constraints define linear relationships between these parameters, allowing for more realistic modeling of correlated uncertainties. By optimizing decisions for the worst-case scenario, robust optimization enhances the resilience of the SC, ensuring its adaptability and performance under highly adverse conditions [7].

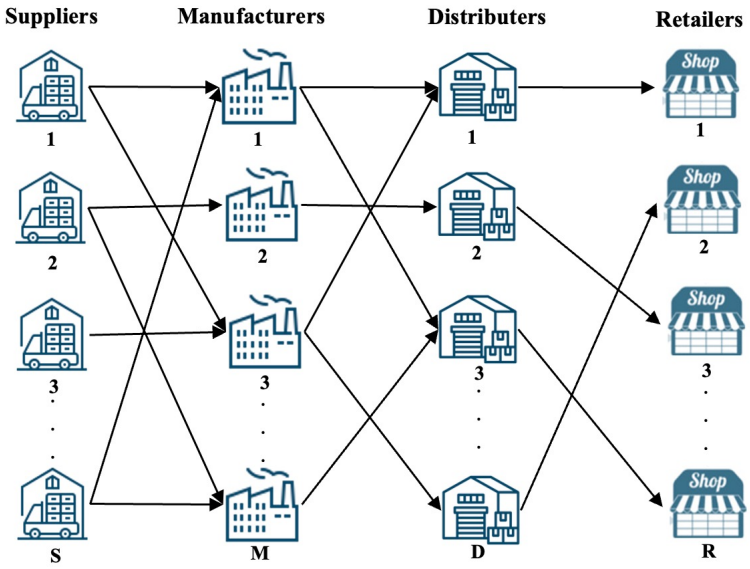


Figure 1: An illustrative structure for the multi-stage SC

Several assumptions are invoked to solve the problem for all models.
- The suppliers, manufacturers, potential distributors, and retailers are known in advance.
- The sum of the capacities of distributors is enough to meet the customer demands.
- Raw materials can be reprocessed according to their quality.
- The parameters other than customer demand and raw material quality are deterministic.

3.2 Two-stage Stochastic Programming Model

In the following, the model along with the indices, variables, and parameters are provided.

Indices

s: Index defined for suppliers (s=1,2...,S)
m: Index defined for manufacturers (m=1,2...,M)
d: Index defined for distributors (d=1,2...,D)
r: Index defined for retailers/customer (r=1,2...,R)
q: Index defined for quality levels (q=1,2...,Q)
t: Index defined for periods (t=1,2...,T)
p: Index defined for scenario (p=1,2...,P)

Here-and-now decision variable

X_{dt}: 1, if the distributor d is utilized during the period t, and 0 otherwise
DL_{drt}: the delivery lead time between the distributor d and the customer r during the period t

Wait-and-see decision variables

A_{smqtp}: the amount of q quality materials transported from the supplier s to the manufacturer m during the period t for the scenario p
B_{mdtp}: the number of products distributed from the manufacturer m to the distributor d during the period t for the scenario p
C_{drtp}: the amount of products delivered from the distributor d to the customer r during the period t for the scenario p
R_{mqtp}: the number of q quality material reprocessed in the manufacturer m during the period t for the scenario p
I^1_{dtp}: the inventory of the distributor d during the period t for the scenario p
I^2_{rtp}: the inventory of the customer r during the period t for the scenario p
BO_{rtp}: the backorder amount of the customer r during the period t for the scenario p
S_{drtp}: 1, if the distributor d supplies products to the customer r during the period t for the scenario p, and 0 otherwise

Parameters

TC^1_{smqt}: the delivering cost of q quality material between the supplier s to the manufacturer m during the period t
TC^2_{mdt}: the delivering cost for products between the manufacturer m to the distributor d during the period t
TC^3_{drt}: the delivering cost for products between the distributor d to the customer r during the period t
Cap^1_{sqt}: the capacity of the supplier s for q quality material during the period t
Cap^2_{mt}: the maximum amount of products that can be processed by the manufacturer m during the period t
Cap^3_{dt}: the maximum amount of products that can be delivered by the distributor d during the period t
D_{rt}: the demand of the customer r during the period t
PC_{sqt}: the acquisition cost of q quality material from the supplier s during the period t
RN_q: the percentage of q quality material for reprocessing

HC^1_{dt}: the holding cost of the distributor d during the period t
HC^2_{rt}: the holding cost of the customer r during the period t
BP_{rt}: the penalty cost of backorders for the customer r during the period t
CO_{dt}: the opening cost of the distributor d during the period t
UC_{mt}: the production cost of the manufacturer m during the period t
W: the total number of utilized distributors
H_p: the occurrence probability of the scenario p
RC_{mqt}: the reprocessing cost of q quality material at the manufacturer m during the period t
LT^1_{smt}: the delivery time between the supplier s and the manufacturer m during the period t
LT^2_{mt}: the production time of the manufacturer m during the period t
LT^3_{mqt}: the reprocessing time of q quality material at the manufacturer m during the period t
LT^4_{mdt}: the delivery time between the manufacturer m and the distributor d during the period t
LT^5_{drt}: maximum delivery time between the distributor d and the customer r during the period t
LT^6_{drt}: minimum delivery time between the distributor d and the customer r during the period t
LT^7_{rt}: Total lead time to the customer r during the period t

Objective Function

$$\min z = \sum_d \sum_t CO_{dt} X_{dt} + \mathbb{E}_\xi Q(x,\xi) \tag{1}$$

$$\begin{aligned}\mathbb{E}_\xi Q(x,\xi) = \sum_p H_p \Big(& \sum_s \sum_m \sum_q \sum_t A_{smqt} TC^1_{smqt} + \sum_m \sum_d \sum_t B_{mdt} TC^2_{mdt} + \\ & \sum_d \sum_r \sum_t C_{drt} TC^3_{drt} + \sum_m \sum_d \sum_t B_{mdt} UC_{mt} + \\ & \sum_m \sum_q \sum_t RC_{mqt} R_{mqt} + \sum_s \sum_m \sum_q \sum_t A_{smqt} PC_{sqt} + \\ & \sum_d \sum_t HC^1_{dt} I^1_{dt} + \sum_r \sum_t HC^2_{rt} I^2_{rt} + \sum_r \sum_t BP_{rt} BO_{rt} \Big)\end{aligned} \tag{2}$$

Constraints

$$\sum_m A_{smqtp} \le Cap^1_{sqt} \quad \forall_{s,q,t,p} \tag{3}$$

$$\sum_d B_{mdtp} \le Cap^2_{mt} \quad \forall_{m,t,p} \tag{4}$$

$$\sum_r C_{drtp} \le Cap^3_{dt} \times X_{dt} \quad \forall_{d,t,p} \tag{5}$$

$$\sum_s \sum_q A_{smqtp} = \sum_d B_{mdtp} \quad \forall_{m,t,p} \tag{6}$$

$$\sum_m B_{mdtp} + I^1_{dt-1p} = \sum_r C_{drtp} + I^1_{dtp} \quad \forall_{d,t,p} \tag{7}$$

$$\sum_d C_{drtp} + I^2_{rt-1p} = D_{rt} + I^2_{rtp} + BO_{rt-1p} + BO_{rtp} \quad \forall_{r,t,p} \tag{8}$$

$$RN_q \sum_s A_{smqtp} = R_{mqtp} \quad \forall_{m,q,t,p} \tag{9}$$

$$\sum_s \sum_m LT^1_{smt} + \sum_m LT^2_{mt} + \sum_m \sum_q LT^3_{mqt} + \sum_m \sum_d LT^4_{mdt} + \sum_d DL_{drt} = LT^7_{rt} \quad \forall_{r,t} \tag{10}$$

$$\sum_d X_{dt} \leq W \quad \forall_t \tag{11}$$

$$DL_{drt} \leq LT^5_{drt} \times S_{drtp} \quad \forall_{d,r,t,p} \tag{12}$$

$$DL_{drt} \geq LT^6_{drt} \times S_{drtp} \quad \forall_{d,r,t,p} \tag{13}$$

$$S_{drtp} \leq X_{dt} \quad \forall_{d,r,t,p} \tag{14}$$

$$\sum_d S_{drtp} = 1 \quad \forall_{d,r,t,p} \tag{15}$$

$$A_{smqtp}, B_{mdtp}, C_{drtp}, R_{mqtp}, I^1_{dtp}, I^2_{rtp}, BO_{rtp}, \ DL_{drt} \geq 0 \quad \forall_{s,m,q,t,p} \tag{16}$$

$$X_{dt}, S_{drtp} \in 0, 1 \tag{17}$$

Equation (1) represents the objective function, which aims to minimize the total cost, including the opening cost of potential distributors, transportation costs, holding costs, and penalty costs. The objective function comprises of two components: the first-stage cost and the expected second-stage cost. The first-stage cost covers the opening cost of potential distributors, which must be decided before the uncertainty occurs. The expected second-stage cost is calculated by considering multiple demand and raw material quality scenarios, each associated with a probability Hp that reflects its likelihood, as represented in Equation (2). In this way, uncertainty is managed through scenario-based representation, and the probabilistic weights Hp assigned to each scenario facilitate the evaluation of expected costs. The probability of each scenario can be calculated from historical data based on its frequency of occurrence. Given the structure of two-stage stochastic programming, the second-stage objective function is minimized for each scenario to determine optimal recourse decisions in response to realized uncertainties. Excluding this minimization step would reduce the second-stage cost to a deterministic value, thereby failing to capture the adaptive and scenario-dependent nature of the model.

Constraint (3) ensures that the total amount of raw materials received from all suppliers does not exceed their available capacity for each scenario. This capacity limitation prevents overloading suppliers and reflects the real-world limitations of supply availability. Constraint (4) satisfy that the total amount of products delivered from the m^{th} manufacturer to the d^{th} distributor cannot exceed the manufacturer's production capacity in any scenario. This guarantees that manufacturers operate within their capacity limits, even under fluctuating demand conditions. Constraint (5) implies that the total number of products delivered from the d^{th}distributor to the r^{th} retailer/customer cannot exceed the capacity of the distributor if that distributor is utilized. Constraint (6) balances the flow between incoming materials to the manufacturer and outgoing products, maintaining inventory flow consistency. Constraint (7) assure that the inventory balance from the m^{th} manufacturer to the d^{th} distributor. The incoming and outgoing quantities must align to maintain accurate inventory levels under all potential conditions. Constraint (8) denotes JIT satisfaction of total demand by considering the scenarios generated to represent comprehensive conditions. It ensures JIT by preventing inventory accumulation and avoiding backorders. Constraint (9) calculates the required reprocessing amounts due to varying raw material quality, which is scenario dependent. Constraint (10) determines the delivery time from the distribution center to the retailers for the final products. Constraint (11)

limits the maximum number of possible distributors that may be opened during the corresponding period. Constraints (12) and (13) ensure that products are delivered from the distributor to retailers within predefined minimum and maximum limits, representing the delivery lead time interval. This guarantees JIT distribution to the retailers. Constraint (14) secures that each retailer obtains products from the open distribution center for each scenario, ensuring demand is always satisfied from available resources. Constraint (15) implies that each retailer supplies products from only one distributor. Lastly, constraint (16) enforces non-negativity for continuous decision variables, while constraint (17) defines binary decisions for distributor utilization and supply relationships, preserving the logical structure of the model.

3.3 Robust Optimization Model

The robust optimization model is developed to manage raw material quality uncertainty without relying on scenario-based representation. Instead, it introduces uncertainty set to define possible variations in raw material quality. Therefore, it is important to state that scenarios are not considered in this model. In this regard, the indices, variables, parameters and constraints (Eq.(3)-Eq.(17)) are consistent with those in the two-stage stochastic programming model, except that the scenario index (p) is removed. Additionally, the variables, parameters, objective function and constraints that differ from the two-stage stochastic programming model are also specified below.

Variables

p_q: the first auxiliary positive variable
q_q: the second auxiliary positive variable
Z_{smqt}: the third auxiliary positive variable

Parameters

Γ_q: uncertainty parameter
$\widehat{a_q}$: deviation from nominal value

Objective Function

$$\begin{aligned}\min z = & \sum_s \sum_m \sum_q \sum_t A_{smqt} TC^1_{smqt} + \sum_m \sum_d \sum_t B_{mdt} TC^2_{mdt} + \\ & \sum_d \sum_r \sum_t C_{drt} TC^3_{drt} + \sum_m \sum_d \sum_t B_{mdt} UC_{mt} + \\ & \sum_m \sum_q \sum_t RC_{mqt} R_{mqt} + \sum_d \sum_t CO_{dt} X_{dt} + \\ & \sum_s \sum_m \sum_q \sum_t A_{smqt} PC_{sqt} + \sum_d \sum_t HC^1_{dt} I^1_{dt} + \\ & \sum_r \sum_t HC^2_{rt} I^2_{rt} + \sum_r \sum_t BP_{rt} BO_{rt} \end{aligned} \tag{18}$$

Constraints

$$RN_q \sum_s A_{smqt} - (p_q \times \Gamma_q + q_q) = R_{mqt} \quad \forall_{m,q,t} \tag{19}$$

$$p^1_q + q^1_q \leq RN_q \times (\hat{a}_q) \times (Z_{smqt}) \quad \forall_{s,m,q,t} \tag{20}$$

$$Z_{smqt} \geq A_{smqt} \quad \forall_{s,m,q,t} \tag{21}$$

Equation (18) is the objective function, which aims to minimize the overall SC cost, including the

opening costs, transportation costs, holding costs, and penalty costs. Constraints (19)-(21) are designed to incorporate the impact of quality uncertainty into the robust optimization model. In this model, raw material quality uncertainty is captured using an interval-polyhedral uncertainty set, which allows the model to account for potential variations in raw material quality within a defined range. The interval-polyhedral uncertainty combines both interval uncertainty (representing bounded variation) and polyhedral uncertainty (representing more complex, multi-dimensional variations), balancing solution robustness and model tractability. This combination provides an effective trade-off between ensuring quality stability and maintaining computational feasibility, which is particularly important for developing optimization model [26]. The uncertainty is represented by the parameter (Γ_q), which defines the bounds of variation for the raw materials. The value of (Γ_q) determines the extent of the uncertainty in the final product's quality, with higher values providing greater protection against possible deviations from nominal quality, thus reducing the likelihood of constraint violations. Specifically, for the first raw material, Γ_1 ranges from 0.04 to 0.10, and for the second raw material, Γ_2 ranges from 0.12 to 0.24. When the values of Γ_1 and Γ_2 are set to 0.04 and 0.12 respectively, the model simplifies into the nominal (deterministic) model, where uncertainty is not considered, and quality variations are neglected. As Γ_q values increase, the model becomes more robust, providing a higher level of protection against uncertainty but at the cost of potentially increasing conservatism in the solution.

4 Computational Study

4.1 A Case Study from a Hazelnut Company in Türkiye

In this study, the proposed two-stage stochastic programming and robust optimization models are validated through a case study involving a hazelnut company in Giresun, Türkiye. The case considers two types of raw materials with different quality levels, namely Giresun quality and Levant quality, sourced from four suppliers located in İstanbul, Ordu, Piraziz, and Giresun. Giresun quality represents the higher quality level, while Levant quality corresponds to the lower quality level. The raw materials can be reprocessed based on their quality, incurring reprocessing costs. Firstly, the raw materials are distributed to the manufacturing facility to produce the final product. Secondly, the final products are then produced in the manufacturing center in Giresun and subsequently sent to potential distribution centers in Kocaeli, Ankara, Denizli, and Diyarbakır. Lastly, the products are delivered to the retailers, i.e., demand points, in 51 different cities in Türkiye. The main purpose is to determine which distribution centers are employed when designing the SC network. That being the case, the objective is the minimization of the overall cost including the opening cost of potential distributors, transportation costs, holding costs, and penalty costs. The real-world SC case study, including the suppliers, manufacturers, and retailers, is illustrated in Figure 2.

In order to analyze the problem from a variety of aspects and find high-quality solutions, the 40 scenarios are designed to capture uncertainty in key parameters, including raw material quality levels and retailer demands, based on real-world observations. These scenarios are created to represent possible future conditions and assess the robustness of the proposed SC network design under different circumstances.

To model demand variability, real sales data from previous years are analyzed to identify the demand distribution for each retailer. It is observed that demand fluctuated within a specific range, following a normal distribution pattern. Figure 3 illustrates this distribution. In the scenarios, retailer demands are generated from a normal distribution N(3885, 595), where the mean (3885) and standard deviation (595) are derived from historical sales records. To ensure realistic values, the generated demands are bounded between 2,500 and 5,000 units, reflecting the range observed in the historical data.

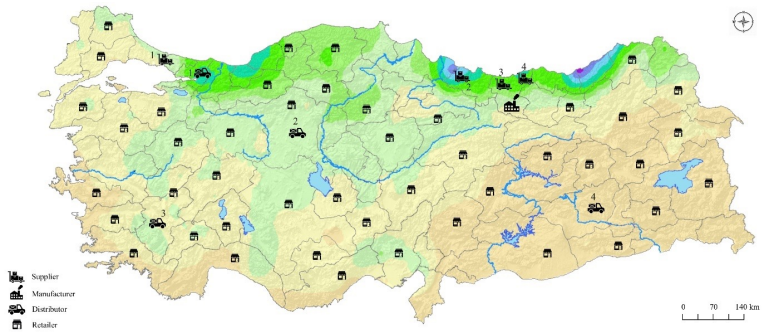


Figure 2: Illustration of the case study

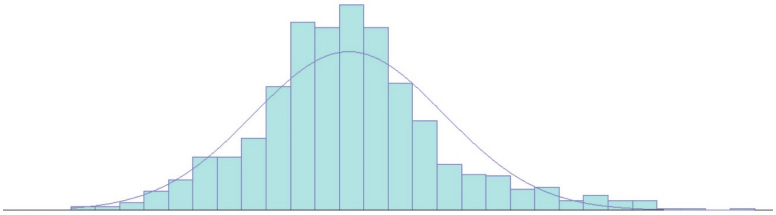


Figure 3: Distribution of historical demand data

Similarly, historical procurement data indicated that the quality levels of raw materials varied within a specific range for both Giresun and Levant types. Based on this real data, random quality parameters are generated for the scenarios. High-quality raw material values are generated between 0.04 and 0.10, while low-quality values ranged between 0.12 and 0.24. These ranges are determined from quality inspection records at the manufacturing facility.

The combination of demand variability and raw material quality parameters resulted in 40 distinct scenarios, each representing a unique combination of demand realizations and raw material quality levels.

In the following, the problem data with descriptions are provided. Whilst Table 2 shows the distribution cost from each supplier to manufacturer per unit of product, the capacities of suppliers are given in Table 3. The capacities of potential distributor presented in Table 4 pave the way for evaluating the distributor opening decisions to satisfy customer demands. The procurement costs of raw materials regarding the quality levels are provided in Table 5 for each supplier.

Table 2: The distribution cost from suppliers to manufacturer

Suppliers	**Manufacturer (Giresun)**
İstanbul	4.98 TL/unit
Ordu	0.24 TL/unit
Piraziz	0.14 TL/unit
Giresun	0.05 TL/unit

The rest of the data along with the scenarios for the real case study is available in the [MSSCD] repository at [https://github.com/data-re/MSSCD].

Table 3: The capacities of supplier

Suppliers	Capacities
İstanbul	70000 unit
Ordu	100000 unit
Piraziz	50000 unit
Giresun	62000 unit

Table 4: The capacities of potential distributors

Distributors	Capacities
Kocaeli	568000 unit
Ankara	569000 unit
Denizli	573000 unit
Diyarbakır	575000 unit

Table 5: The procurement cost of raw material with respect to quality

Suppliers	Quality Level	January	April	August	December
İstanbul	GiQu	35.8	36.3	35.8	33.1
İstanbul	LeQu	32.3	34.8	31.7	30.6
Ordu	GiQu	43.8	40.5	38.9	39.4
Ordu	LeQu	40.8	38.5	35.9	36.3
Piraziz	GiQu	41.9	38.4	37.1	38.6
Piraziz	LeQu	40.9	37.8	36.1	37.2
Giresun	GiQu	39.4	37.2	39.6	41.5
Giresun	LeQu	38.8	36.4	36.9	40.7

4.2 Computational Analysis

In this part, detailed computational results are provided to explore the important aspects of the multi-period multi-stage SC design under uncertainty for just-in-time distribution. To this end, a set of experiments are executed through both the stochastic programming and the robust optimization models coded in GAMS 23.5/CPLEX optimization package. A computer with the Intel® Core TM i5-1135G7 CPU and 8 GB memory is employed to solve the problems by executing the models. By doing so, important managerial insights are revealed by considering the uncertainty inherent in the SC.

4.3 Results Obtained through Deterministic Model

The deterministic model is obtained to make fair comparison by eliminating the scenarios from the stochastic model. That is, if the scenario index is removed from the stochastic model, the deterministic model is constructed. In the following, the results achieved by the deterministic model are presented.

As a result of the deterministic model aims to minimize the overall cost, the quantities of raw materials arriving at the manufacturing facility are given in Tables 6-8 according to their quality respectively. A total of 554729 units of raw material is provided for the products that need to be produced to meet the demands of retailers. While 299355 units are Giresun Quality raw material, 255374 units are Levant quality raw

material. In other words, 54% of the supplied raw material is the first quality, while 46% consists of second quality raw materials.

Table 6: The number of raw materials with Giresun quality

Suppliers	January	April	August	December
İstanbul	6879.57 unit	-	-	68475.55 unit
Ordu	-	-	-	-
Piraziz	-	50000 unit	50000 unit	-
Giresun	62000 unit	62000 unit	-	-

Table 7: The number of raw materials with Levant quality

Suppliers	January	April	August	December
İstanbul	70000 unit	-	-	70000 unit
Ordu	-	-	87951,22 unit	-
Piraziz	-	-	-	-
Giresun	-	-	27423,04 unit	-

Table 8: The amount of reprocessed raw materials

Quality Levels	January	April	August	December
Giresun	4821,57	7840	3500	4793,29
Levant	11900	4661,92	14951,71	11900

The reprocessed quantities of the supplied raw materials are given in Table 8 for all periods. While a total of 20954 units of purchased Giresun quality hazelnuts are reprocessed, a total of 43413 units of Levant quality hazelnuts are reprocessed.

Based on the results generated from the deterministic model, the demands of the retailers are met by opening distributors in Kocaeli, Ankara, and Diyarbakır among four possible distribution centers. Although utilizing three distributors increases the fixed cost, it ensures that the delivery is made on time, and it guarantees that the enterprise gets rid of the penalty costs that may cause the loss of customers.

4.4 Results Obtained through Two-stage Stochastic Programming Model

The results produced by the stochastic programming model shows that while the distributors in Kocaeli, Ankara, and Diyarbakır are opened in all solutions for each scenario separately, the distribution center in Denizli is not opened. Notably, the objective function values with respect to the scenarios are reported in Table 9. Besides, in 30 of the 40 scenarios, Giresun quality hazelnut is preferred more than Levant quality hazelnut by retailers.

Here, five concepts are employed to perform the scenario analysis: (i) the expected value (EV) of perfect information (EVPI), (ii) the wait-and-see solution (WS), (iii) the recourse problem solution (RP), (iv) expected result of using the EV solution (EEV), and (v) the value of stochastic solution (VSS). These terms are briefly explained in below.

Table 9: The objective function values with respect to scenarios

Scenarios	Obj. function	Scenarios	Obj. function
Scenario 1	56930138	Scenario 21	57308469
Scenario 2	56315013	Scenario 22	56853450
Scenario 3	56330228	Scenario 23	56153877
Scenario 4	56715773	Scenario 24	55445127
Scenario 5	57320630	Scenario 25	57409480
Scenario 6	57392006	Scenario 26	56625061
Scenario 7	56488641	Scenario 27	56800412
Scenario 8	56809085	Scenario 28	57958746
Scenario 9	56679687	Scenario 29	55575271
Scenario 10	57130712	Scenario 30	57115234
Scenario 11	55760334	Scenario 31	56939092
Scenario 12	57232263	Scenario 32	56949768
Scenario 13	57488076	Scenario 33	56761975
Scenario 14	56586070	Scenario 34	57383694
Scenario 15	55788284	Scenario 35	56820463
Scenario 16	58505639	Scenario 36	56843805
Scenario 17	57189860	Scenario 37	57721132
Scenario 18	56081012	Scenario 38	55774035
Scenario 19	56786626	Scenario 39	56373676
Scenario 20	56890610	Scenario 40	57312136

The EVPI represents the potential loss of profit associated with uncertainty. It measures the cost of obtaining perfect information for all factors influencing the SC design and is calculated as the difference between RP and WS. The WS corresponds to the EV of the overall cost in case the wait-and-see results are known beforehand. If we know the wait-and-see decisions before making our decision, we can make the best decision. In other words, WS can be regarded as a relaxation of the stochastic model. The RP corresponds to the result of the 'here-and-now' solution, which represents the value of the stochastic optimization problem within all scenarios and uncertainties. The EEV indicates the expected true objective function value under uncertainty when all variables are assumed to be the same. The VSS represents the potential benefit derived from solving stochastic model and evaluates the value of utilizing probability distributions for future outcomes. It is computed by subtracting the value of EEV from the value of RP. Finally, it is checked whether these obtained values provide the inequalities in Madansky [19] for validation purpose and are shown in Table 10.

Table 10: Inequalities regarding the stochastic problem

Inequalities	Values
$WS \leq RP \leq EEV$	$5613639.72 \leq 56814013.09 \leq 56814013.09$
$0 \leq EVPI, 0 \leq VSS$	$0 \leq 373.37; 0 \leq 0$
$VSS \leq EEV - EV$	$0 \leq 56814013.09 - 56803738.41$
$EVPI \leq EEV - EV$	$373.37 \leq 56814013.09 - 56803738.41$

Another analysis is the comparison of the results achieved by the stochastic models solved for different

numbers of scenarios, with the result of the deterministic model. As known, the data generated for 40 scenarios are used in 5, 10, 15, 20, 25, 30, and 35 scenarios. The largest amount of deviation in the positive direction occurred with the rate of 32.2%, when 15 scenarios are assumed to be realized. In this case, the enterprise has an excess cost of 68148.62 TL. The largest deviation for the negative direction is the situation where 20 scenarios are assumed to be realized with a rate of 8.9%. In this case, the enterprise has a lower cost of 18910.52 TL.

Figure 4 illustrates the deviation values for different number of scenarios. As observed in the figure, the deviation decreases with an increasing number of scenarios. This reduction can be attributed to the model's ability to more thoroughly capture the underlying uncertainties. By incorporating a greater number of scenarios, the model accounts for a wider range of potential outcomes, which allows for a more accurate representation of the uncertainty inherent in the system. As a result, the model can generate more reliable and realistic solutions, minimizing the impact of extreme or less likely scenarios.

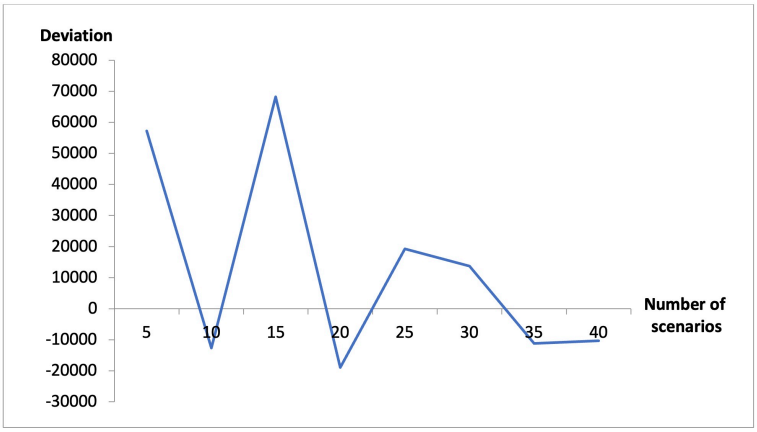


Figure 4: Comparison of deviation values across different number of scenarios

4.5 Results Obtained through Robust Optimization Model

The results achieved by the robust optimization model are reported in this section. After solving the optimization model, the number of raw materials acquired by the suppliers for both Giresun and Levant quality raw materials are presented in Tables 11 and 12. It is monitored that the enterprise meets 51.7% of the total raw material supplied from Giresun quality hazelnuts, while the remaining amount is met from Levant quality hazelnuts. Furthermore, it is found that distributors are opened in Kocaeli, Ankara, and Diyarbakır for all reprocessing rates associated with the uncertainty parameter. The main reason behind it is to meet the maximum amount of demand.

Table 11: The number of raw materials received from suppliers for Giresun quality

Suppliers	January	April	August	December
İstanbul	-	50000	50000	6606
Ordu	-	130	130	-
Piraziz	7010	-	-	62000
Giresun	62000	62000	-	-

Table 12: The number of raw materials received from suppliers for Levant quality

Suppliers	January	April	August	December
İstanbul	-	-	35179	11507
Ordu	11507	-	35179	35179
Piraziz	35179	-	17951	35179
Giresun	35179	27782	-	-

The values of the uncertainty parameter (Γ) determine the extent of the raw material reprocessing ratio. For instance, the values to 0.04 and 0.12 for Γ_1 and Γ_2 respectively indicate that the uncertainty caused by the quality of raw materials is not considered when designing the multi-period multi-stage SC. The way these parameters are considered can directly impact the SC design. The amount of reprocessed raw materials, which increases as raw material quality decreases, leads to a significant increase in quality costs and penalty costs when the product of desired quality is not delivered to the customer in a JIT manner. Therefore, the total SC cost also increases at the same rate.

The objective function generated regarding the uncertainty parameters $\Gamma_1$and Γ_2 are depicted in Figure 5, where the horizontal axis is devoted to the parameter Γ_2 and each color corresponds to different values of the parameter Γ_1. As can be easily understood from this figure, the overall cost is negatively affected as the parameter values increase to protect the model from uncertainty. In other words, larger Γ_q values indicate greater the price of robustness values as it shown in Figure 6. Here, "the price of robustness" refers to the cost value that the enterprise can afford against uncertainties [7].

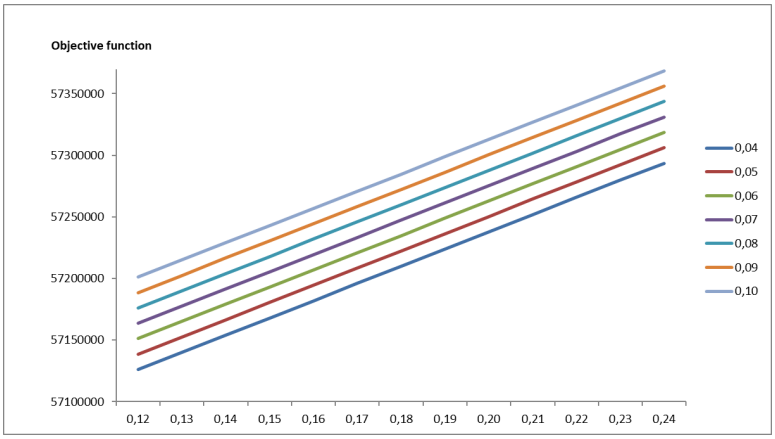


Figure 5: The objective function considering the uncertainty parameters Γ_1 and Γ_2

On top of that, the probability of constraint violation (PoV) values with respect to Γ are drawn in Figure 7. From this figure, it is observed that the maximum protection is assured when the quality ratio is set at 0.30. However, the trend remains consistent for the PoV values corresponding to quality ratios between 0.24 and 0.30. Therefore, it is important to note that a value of 0.24 also provides adequate protection against constraint violations arising from uncertainty in quality levels. The PoV value is calculated by equation $e^{(-\Gamma^2/2|N|)}$ [31].

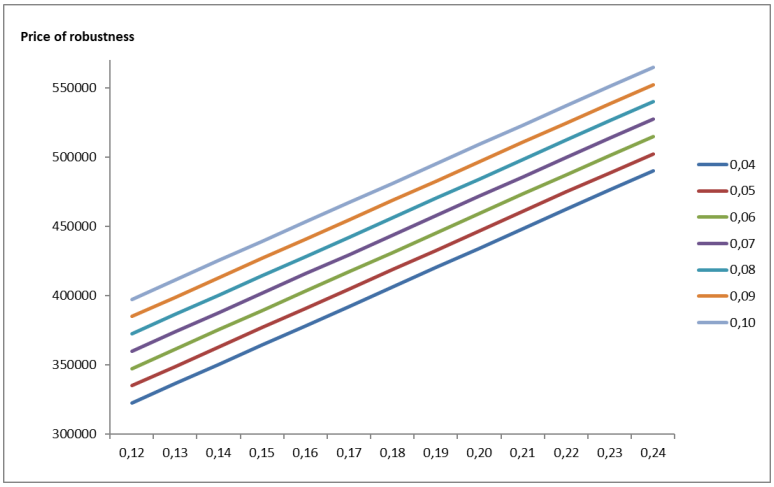


Figure 6: The price of robustness w.r.t the parameters Γ_1 and Γ_2

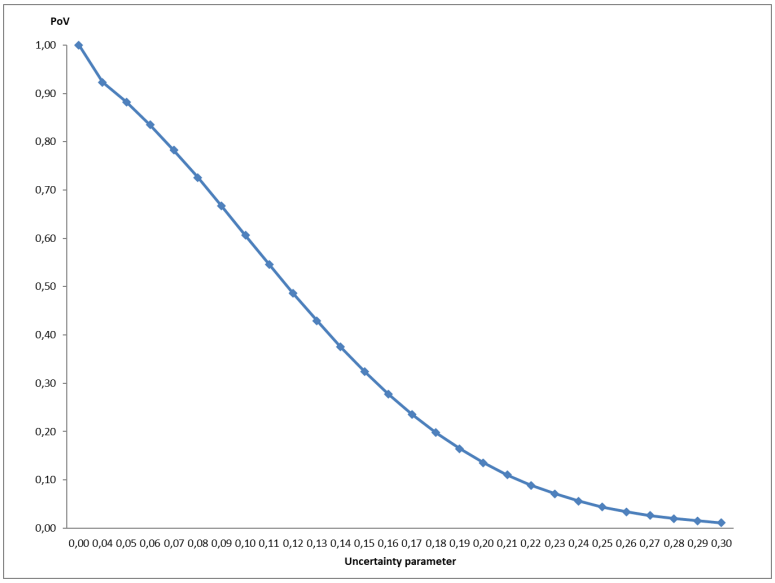


Figure 7: The probability of constraints violation w.r.t the uncertainty parameter

5 Findings and Managerial Insights

The computational analysis reveals key findings and managerial insights regarding the multi-period, multi-stage resilient and sustainable SC network design, focusing on JIT distribution under demand and raw material quality uncertainty. These findings are organized to answer the research questions posed.

• Effect of raw material quality on SC Performance and Cost:

Raw material quality significantly influences the optimization results. The analysis shows a clear preference for high-quality raw materials across all models. In the deterministic model, high-quality raw materials account for 54% of the total raw material supply, while in the stochastic model, high-quality materials are preferred in 30 out of 40 scenarios, averaging 55%. The robust model, despite focusing on worst-case scenarios, still favors high-quality raw materials at an average rate of 52%.

The consistent preference for high-quality raw materials underscores the importance of maintaining high standards in raw material procurement, which directly impacts the SC's ability to meet customer demands reliably. While high-quality materials increase purchasing costs, they reduce the likelihood of delays and reprocessing, ensuring JIT deliveries and contributing to a more resilient SC. This reduces operational disruptions, enhancing the system's overall sustainability by minimizing waste and inefficiencies.

• Impact of Demand and Raw Material Quality on Strategic Decisions

Both demand and raw material quality uncertainties significantly influence strategic decisions. The findings from all optimization models (deterministic, stochastic, and robust) suggest that opening distributors in Kocaeli, Ankara, and Diyarbakır is a robust strategy for meeting customer demands on time while minimizing costs. These locations are strategically chosen to reduce transportation costs and ensure timely delivery, making them ideal for a JIT SC network. The models also emphasize the importance of prioritizing high-quality raw materials to maintain SC efficiency and resilience under varying conditions. By focusing on robust and resilient strategies—such as selecting optimal locations and prioritizing high-quality materials—companies can ensure a sustainable SC that delivers long-term value, maintains high service levels, and reduces risks associated with demand and quality uncertainties.

• Comparison of Optimization Models:

Deterministic model: Offers the lowest cost solution, assuming known and fixed conditions. This model provides the most cost-effective option but does not account for variability in demand or raw material quality.

Two-stage stochastic programming model: Incorporates demand and raw material quality uncertainty, offering a solution that balances cost and risk. The results are similar to the deterministic model in terms of distributor locations but show variations in raw material preferences across different scenarios.

Robust Model: Focuses on minimizing risk by preparing for the worst-case scenario, which is a core feature of robust optimization. The worst-case scenario is determined by modeling the most extreme potential fluctuations in raw material quality, ensuring the solution remains effective under highly uncertain conditions. By prioritizing the worst-case scenario, the robust model adopts a conservative approach, favoring decisions that maintain system functionality even in the face of extreme uncertainty. As a result, while the model slightly reduces reliance on first-quality raw materials in favor of more reliable sourcing, it still selects first-quality materials at an average rate of 52%.

The key differences between the models lie in how they balance cost and risk. The deterministic model is ideal for stable conditions, while the stochastic and robust models offer more resilience under uncertainty, making them more suitable for industries facing fluctuating demands or quality issues.

• Key considerations for SC managers under uncertainty:

Uncertainty in demand: Managers should account for variability in customer demand when making decisions about distributor locations and JIT distribution. By using the two-stage stochastic programming

model, managers can better plan for demand fluctuations, ensuring that the SC remains responsive and adaptable, which is critical for maintaining a resilient and sustainable operation.

Uncertainty in raw material quality: Raw material quality uncertainty affects the ability to deliver products on time and at the desired quality. The robust model highlights the need to plan for worst-case scenarios in raw material quality, ensuring the SC can still function even under adverse conditions, thus reinforcing both resilience and sustainability.

SC managers should prioritize building flexibility into their operations. This includes securing high-quality raw materials, diversifying supplier sources, and ensuring distributors are strategically located to minimize risk. Investing in resilience systems that can adapt to fluctuations in demand and supply quality will help maintain JIT performance and cost efficiency.

6 Conclusion

This study addresses the multi-period multi-stage SC design problem for just-in-time distribution under uncertainty. The stochastic programming and the robust optimization models are developed to represent the problem mathematically. Whilst the scenario approach is used to cope with the demand and quality rate uncertainty for the two-stage stochastic programming model, the worst-case scenario method is applied for the robust optimization model to obtain a solution that meets all requirements, even in extreme conditions. Being thus motivated, two different approaches are employed through a real-world case study from an enterprise in Giresun/Türkiye, and solutions are analyzed independently from each other. According to the computational results, the benefits of supplying high-quality raw materials, i.e., Giresun quality, leads to better solutions in terms of the cost criterion. The impact of the raw material quality is felt much more under the demand uncertainty. In addition, three cities Kocaeli, Ankara, and Diyarbakır in Türkiye are selected to open distributors according to both the deterministic model and other models associated with the uncertainty.

The major contributions of the paper are as follows: (i) To the best of authors knowledge, the SC design is addressed under uncertainty in the raw material quality by considering the just-in-time distribution for the first time. (ii) A case study from a company in Giresun/Türkiye is analyzed. (iii) Managerial insights are provided through the stochastic and robust optimization models.

Despite the contributions of this study, several limitations should be acknowledged: (i) The stochastic and robust optimization models are addressed separately rather than in an integrated framework, which may limit the ability to capture interactions between different uncertainty types simultaneously. (ii) The analysis considers uncertainty only in demand and raw material quality. Other relevant uncertainties, such as reprocessing times, distribution times, or supply disruptions, are not included, which could affect the robustness of the solutions in practice. ii) The case study is limited to a single enterprise in a specific region and industry, which may constrain the generalizability of the results. Future studies could apply and validate the models in other industries or geographic contexts to enhance broader applicability.

Addressing these limitations in future research could improve the comprehensiveness, robustness, and practical relevance of the proposed methodologies.

Author Contribution Statements

All authors contributed equally to the writing of this paper.

Declaration of Competing Interests

The authors declare that they have no competing interests.

Data Availability Statement

The dataset supporting the findings of this study is available in the [MSSCD] repository at [https://github.com/data-re/MSSCD].

Funding Source Declaration

No funding was received for conducting this study.

Ethical Standard

This article does not contain any studies with human participants or animals performed by any of the authors.

Declaration of Generative Artificial Intelligence Use

The authors declare that no generative Artificial Intelligence tools were used in the preparation of this manuscript.

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