

Supplier selection and order allocation in sustainable closed-loop supply chains with product perishability and supplier uncertainty

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ABSTRACT

Context—In the contemporary business environment, characterized by intense competition and rapid global shifts, effective and sustainable supply chain management (SCM) has become a paramount necessity. It is evident that organizations are increasingly relying on Closed-Loop Supply Chains (CLSCs) to enhance the efficiency of material and financial flows while incorporating recycling and reuse practices. The healthcare sector requires a nuanced approach to managing perishable products, especially balancing operational efficiency with environmental sustainability.

Objective—The present study proposes a novel optimization model for order allocation within a CLSC to facilitate the design of a sustainable supply chain network. The objective of this research is to manage uncertainties in supplier capacity while monitoring the storage duration of perishable goods to optimize their dispatch to recycling centers.

Method—The research employs a multi-stage hybrid methodology. As a mathematical model, a scenario-based Mixed-Integer Linear Programming (MILP) model has been developed to address the challenges posed by demand and capacity fluctuations. As a criteria framework, the evaluation of suppliers is conducted based on the Lean, Agile, Resilient, and Green (LARG) principles, along with considerations specific to the pandemic. As a decision-making algorithm, the Full Consistency Method (FUCOM) is used for objective criteria weighting. Intuitionistic Fuzzy Sets (IFS) are used to evaluate expert opinions

based on their professional experience. The Complex Proportional Assessment (COPRAS) method is utilized to evaluate and rank suppliers. As an application, the model's validation is achieved through a case study involving the network design of a hospital in Türkiye.

Results—The findings, supported by an extensive sensitivity analysis on factors such as supplier scores, product shelf life, and capacity, indicate that supplier selection is the most pivotal factor in optimizing the performance of a closed-loop supply chain. The proposed model has been designed to manage the inventory of perishable goods, ensuring timely intervention before expiration. The integration of LARG-based supplier scores into the MILP model has been demonstrated to significantly enhance the responsiveness of the network.

Conclusion—This study emphasizes the pivotal role of strategic supplier selection and effective inventory management in ensuring sustainable healthcare operations. The comprehensive approach presented offers a resilient framework for decision-makers to maintain long-term sustainability and operational agility in a post-pandemic world.

Key Words— MILP, Order allocation, Perishability, Supplier selection, Supplier uncertainty



I. INTRODUCTION

The development of transportation systems has played a crucial role in improving mobility and accessibility. However, the global COVID-19 pandemic has substantially affected mobility and public transport accessibility. The pandemic has resulted in significant economic and social disruptions, with particularly severe consequences for the supply chain and logistics sectors. Quarantine measures and restrictions have imposed operational constraints, caused shipment delays and introduced considerable uncertainties in procurement processes, supplier performance, and consumer behavior [1]. As a result, organizations have faced increased risks, challenging their ability to maintain efficient and resilient supply chain operations [2]–[5]. Notably, the disruptions have affected the operations of nearly 94% of the Fortune 1000 companies [6].

Logistical obstacles, including worker health concerns, reduced container traffic, and suspended transportation services, have introduced significant risks to business viability [7]. These issues highlight the critical role of rapid communication and transportation within logistics management [8], [9]. While tactical and reactive strategies may provide temporary relief, organizations must adopt proactive management approaches to establish more resilient supply chain networks [10]. In addressing these challenges, recent research presents the Lean, Agile, Resilient, and Green (LARG) supply chain framework. This framework focuses on waste reduction (Lean), rapid responsiveness to market dynamics (Agile), adaptability to disruptions (Resilient), and minimizing environmental impacts (Green). A LARG-based supply chain aims to eliminate all forms of waste, enhance responsiveness to market changes, automate responses to disruptions, and decrease the negative environmental effects of operational processes [11]. Integrating LARG principles is crucial for crisis management, as it supports adaptive responses to operational disruptions.

Supply chain sustainability involves balancing multiple, often conflicting factors. Key considerations include environmental impact, social responsibility, economic viability, and ethical obligations. Achieving equilibrium among these dimensions is critical for the long-term resilience and success of supply chains [12]. Balancing the LARG paradigms is particularly important for sustainability across industries. However, equal emphasis on all elements can be challenging and may require trade-offs. For example, Lean's emphasis on minimal inventory may conflict with agile's need for safety stock, illustrating the complexity of integrating different paradigms within sustainability frameworks [11], [13]. Decision-makers should tailor the LARG configuration to their supply chain's specific needs [14]. Ultimately, the long-term profitability of companies depends on the gradual adoption and integration of diverse sustainability perspectives [15].

The increasing complexity of global supply chains, intensified by recent systemic disruptions, requires integrating LARG paradigms into supplier selection frameworks. This integration is essential to advancing Closed-Loop Supply Chains (CLSCs), which aim to balance operational cost-efficiency with broader sustainability and corporate social responsibility goals. "A CLSC is defined as the design, control, and operation of a system to maximize value creation over the entire life cycle of a product with dynamic recovery of value from different types and volumes of returns over time" [16]. In critical sectors such as healthcare, implementing these frameworks is essential. Maintaining supply continuity while addressing resource capacity uncertainty is crucial for both operational efficiency and organizational survival. Therefore, CLSCs in this context must balance cost-effectiveness with dynamic value recovery and risk mitigation across all stages of the product lifecycle.

This research synthesizes the existing literature to identify 19 sub-criteria, encompassing traditional, social, LARG, and

pandemic-specific factors (see Appendix-A), for evaluating supplier performance. These criteria are analyzed using a two-stage hybrid model that integrates Multi-Criteria Decision-Making (MCDM) through the IFS-FUCOM-COPRAS methodology with Mixed-Integer Linear Programming (MILP). The framework is validated with real-world data from a hospital network in Türkiye, focusing on perishable commodity flows. The model employs a scenario-based approach to address capacity fluctuations and introduces a systematic mechanism for tracking inventory waste, thereby narrowing the gap between theoretical optimization and practical clinical application.

Although significant advancements have occurred within specific areas of supply chain management, a comprehensive review of the literature indicates a persistent gap in the simultaneous management of operational and qualitative variables. Existing frameworks often treat supplier selection and order allocation as separate processes, neglecting key factors such as resource capacity uncertainty, product perishability, and input from multiple experts. This research introduces a methodology that addresses fragmentation by integrating diverse elements into a unified, resilient decision-making structure. The principal contributions of the research are outlined below:

- **Integrated Decision-Making Architecture:** This research proposes a two-stage hybrid framework to bridge the gap between qualitative supplier evaluation and quantitative order allocation. Implementing this framework is expected to achieve coherent optimization throughout the supply chain.
- **Multifaceted Risk Evaluation:** This study identifies and applies a comprehensive set of 19 sub-criteria that synthesize traditional economic metrics with LARG paradigms, as well as pandemic-specific risk factors.
- **Stochastic Capacity and Perishability Modeling:** The research develops a mathematical model to address fluctuations in resource capacity using a scenario-based approach, while concurrently managing the specific constraints associated with perishable commodity flows.
- **Empirical Validation in Healthcare:** The model's practical efficacy is demonstrated through a case study in the Turkish healthcare sector, illustrating the translation of theoretical modeling into crisis-resilient operational strategies.

A. Literature review

This study introduces an integrated framework that incorporates LARG criteria alongside traditional performance metrics. It examines the relationship between supplier evaluation and network optimization to provide a comprehensive perspective on the complexities of contemporary CLSCs.

To establish a structured theoretical foundation, a systematic review of the Web of Science Core Collection was conducted. This process aimed to position the model within current academic discourse and to ensure alignment of the study's parameters with established literature. The search strategy utilized targeted keywords such as "network," "supplier selection," "allocation," and "closed" to identify pertinent literature. To maintain a focus on integrated decision-making, studies lacking MCDM techniques were excluded, ensuring alignment with the hybrid methodological framework of this research.

The literature review observed that researchers have studied deterministic models based on exact and fixed parameter values and models that take uncertainty into account. Deterministic models assume exact and constant parameter values, whereas research addressing uncertainty incorporates stochastic, robust, fuzzy, and grey methodologies. Table 1 provides a detailed summary of key studies in literature, categorized by several critical factors: the uncertain parameters they address, the components of the objective functions proposed, the stakeholders involved in reverse flows, the MCDM methods employed, and, when applicable, the real-world products

Table 1. A literature review on supplier selection and closed-loop supply chain network design problems.

Ref.	Model	Uncertain parameter	Objective	MCDM & fuzzy sets	Case study component
[17]	GP	Demand, reverse flows	Profit, supplier score	FST, AHP	Mobile phone
[18]	MO-MINLP	Demand	Profit, supplier score, emission	F-AHP, TFN	Computer
[19]	MO-MILP	Demand, reverse flows	Profit, supplier score	TFN	Mobile phone
[20]	MO-MILP	Demand, reverse flows	Supplier score, cost, emissions	AHP	Electronic product
[21]	MO-MILP	-	Profit, supplier score, defect rate	FST, TFN	Hypothetical
[22]	FLP	Demand	Cost, supplier score, profit	TFN, DEA	Hypothetical
[23]	MO-MILP	Undefined	Revenue, supplier score, failure	Grey theory	Electronic
[24]	NFGP	Demand, quantity discount	Purchase, business opportunity, network cost, environmental impact	F-BWM	Apparel
[25]	Hybrid robust possibilistic flexible programming	Demand, returns	Cost, carbon emissions and water consumption effects, total jobs created	HRFPFH	Apparel
[26]	PHFP	Costs	Cost, defect	PFNs	Hypothetical
This study	Probabilistic MILP	Capacity	Cost, distance from supplier score	IFS, FUCOM, COPRAS	Hospital

featured in case studies. Notably, most studies adopt the Multi-Objective Mixed Integer Linear Programming (MO-MILP) approach, with a significant number also utilizing the Multi-Objective Mixed Integer Nonlinear Programming (MO-MINLP) framework. Uncertainty is most frequently modeled through demand and operational cost parameters. The objective functions in these mathematical models typically focus on cost efficiency, supplier evaluation scores, profit maximization, and emission reduction. Previous research has addressed uncertainty conditions in isolation, focusing either on demand uncertainty [17], [18], [27], [28] or supply uncertainty related to product returns [19], [20], [25], [29], [30].

In the research, few studies address perishability, a significant aspect. Among the reviewed literature, Momenitabar et al. (2023) propose a fuzzy multi-objective Mixed-Integer Nonlinear Programming (MINLP) model that considers the perishability of blood products by minimizing total costs and maximizing patient service levels [31]. Another study addressing perishability in the literature is Varshney et al. (2024), which proposes a mathematical model to minimize transportation costs by optimizing cold storage usage, inventory management, and space allocation strategies [26]. The study also aims to minimize the number of errors occurring during transportation within the supply chain. The applicability of the proposed model is shown using a hypothetical example incorporating cold storage.

Studies in the literature that integrate Mixed-Integer Linear Programming (MILP) with supplier scoring generally focus on criteria sets covering sustainability, technical capability, and operational performance. However, studies that directly address a LARG-oriented approach are quite limited. In most of these studies, like our research, the weights obtained through multi-criteria decision-making (MCDM) methods (such as AHP, Fuzzy Logic, and Grey Theory) are combined into mathematical models as input parameters [18]–[21], [23]. In the present study, supplier scoring is addressed through the integration of IFS-FUCOM-COPRAS, thereby diversifying the evaluation methodology and establishing a more comprehensive decision-making framework. Also, within the reviewed literature, only one study incorporates the experience levels of decision-makers into the scoring process, presenting a structure similar to the perspective adopted in this study [19]. Whereas most existing studies maximize supplier performance scores using multi-objective functions, the present study presents a methodological distinction by proposing a single-objective optimization model that penalizes suppliers for deviations from target levels.

Furthermore, this study develops an inventory structure that explicitly accounts for product perishability, which is often overlooked in the existing literature. Accordingly, it seeks to address a significant gap at both the strategic level, including supplier selection and evaluation, and the operational level, encompassing inventory and procurement planning.

II. PROPOSED MATHEMATICAL MODEL

This section provides a formal description of the problem and outlines the theoretical framework underlying the developed mathematical model. To systematically address uncertainties and mostly subjective judgments in supplier performance evaluation, an analytical approach is introduced that integrates Intuitionistic Fuzzy Set (IFS) theory with Multi-Criteria Decision-Making (MCDM) methods. The model is validated through a comprehensive case study, and a sensitivity analysis is conducted to assess its robustness and stability.

B. Formal problem description

In the framework of this study, the closed-loop supply chain network design and order allocation problem is defined within the logistics network $G = \{V, A\}$. In this network representation, $V = \{S, W, M, R\}$ are the nodes/actors involved in the problem. The nodes include suppliers $S = \{1, 2, \dots, |S|\}$, warehouses $W = \{1, 2, \dots, |W|\}$, demand points $M = \{1, 2, \dots, |M|\}$ and recycling centers $R = \{1, 2, \dots, |R|\}$. The direct flows between these nodes are represented by set A . There are direct product flows from suppliers to warehouses, from warehouses to demand points, and between warehouses. Additionally, direct flows exist from warehouses to recycling centers for products that have reached the end of their shelf life and are no longer fit for use. These flows facilitate both forward and reverse logistics, ensuring that products are efficiently distributed while also addressing sustainability through the recycling of expired goods.

In this problem, a single product type is considered perishable. The study involves a finite planning horizon with a multi-period time frame ($T = \{1, 2, \dots, |T|\}$). The supply capacities of suppliers may vary and are addressed through scenarios ($I = \{1, 2, \dots, |I|\}$). It is assumed that the probability of each scenario $i \in I$ occurring is known and denoted by p_i . The parameter cap_{si}^t whose value is known at the beginning of the planning horizon represents the capacity of supplier $s \in S$, at the beginning of period $t \in T$ under each scenario $i \in I$. Product flows from suppliers to warehouses in batches. It is assumed that the warehouses have no inventory at the start of the planning horizon. The market demand, dem_m^t , is known at the beginning of each period $t \in T$ for each demand center $m \in M$ and must be fully satisfied. is met through only one warehouse.

Each warehouse $w \in W$ can hold inventory up to its storage capacity b_w . If needed, products can be transferred from one warehouse to another, where the transportation cost for moving one unit of product from warehouse a to b , where $(a, b) \in W$ and $a \neq b$, is denoted by $c3_{ab}$. Inventory is managed using the First-In, First-Out (FIFO) method, meaning that the products that enter the warehouse first are also the first to be allocated to demand.

The examined product can be stored in the warehouse along its shelf life. While the maximum storage duration/shelf life ($shlf$)

of the product in the warehouse is assumed to be greater than two periods, any product not dispatched for distribution before its shelf life expires is considered waste. Products whose shelf life has expired in each warehouse $w \in W$ are directed to the recycling center at a penalty and secondary market shipping cost sc_w . A recycling center is designated for waste products from each warehouse. The supplier is responsible for directing the accumulated waste products at the recycling center to either remanufacturing or disposal centers.

In the management of the unpredictable supply of perishable goods, a series of crucial decisions must be made concerning various operational issues, such as demand management, order placement, capacity allocation, and waste tracking. Orders are typically grouped and sent to suppliers before being distributed to demand points and warehouses. Given the perishable nature of the products, close monitoring of warehouse inventory is essential. This involves identifying and tracking items nearing the end of their shelf life to promptly redirect them to recycling facilities, ultimately reducing waste and enhancing supply chain efficiency.

The goal of the problem is to minimize transportation, holding, and waste costs for each supplier $s \in S$ under uncertain supply conditions, considering the supplier evaluation score parameter p_s . The model finds traditional, social, LARG-focused, and pandemic-specific criteria, and suppliers are scored using mathematical methods. All suppliers are rated relative to the most suitable supplier according to the criteria evaluated, and these score parameters are included in the objective function to encourage procurement from highly rated suppliers. The overall structure of the network design can be seen in Fig. 1.

C. Mathematical model

This section presents the mathematical model for an integrated closed-loop supply chain under uncertain supply conditions, specifically for perishable products. The model aims to optimize supplier selection, order allocation, and waste management. The objective is to minimize the total costs, including transportation, holding, and waste disposal, while ensuring efficient supply chain operation. This model is based on the foundational works of Ghiani et al. (2013) and Chopra (2016), with adaptations for inventory and waste tracking constraints inspired by Soysal et al. (2015) [32]–[34]. The model encapsulates the complex dynamics of an integrated closed-loop supply chain, considering the

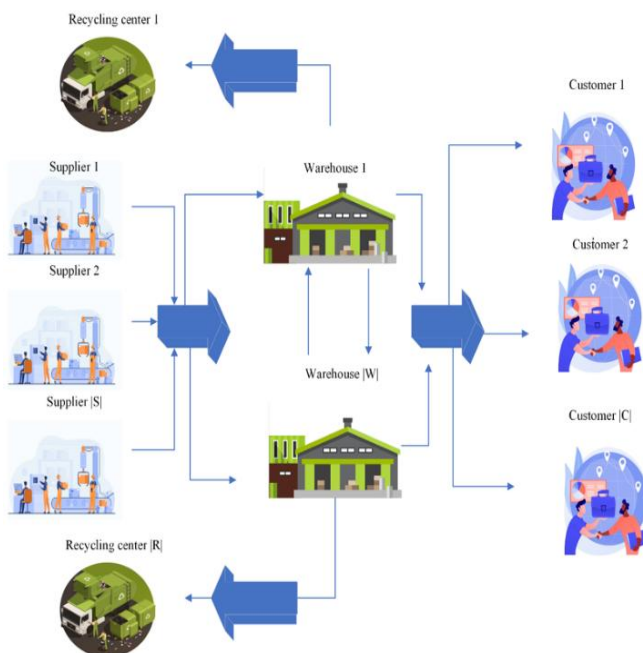


Figure 1. An example of the closed-loop supply chain network design [35].

perishability of products, supply uncertainties, and multiple cost factors. The objective function aims to minimize the total costs while incorporating supplier scores to promote efficient supplier selection and order allocation. The notation table of the proposed mathematical model is presented in Table 2.

As shown in (1), the objective function is designed to minimize costs and consists of six components. The initial part of the function computes the transportation cost for products shipped from suppliers to warehouses). This calculation considers the order batch size, the number of orders placed, and the unit transportation cost per product.

Objective function,

$$Z_{min} = Z_1 + Z_2 + Z_3 + Z_4 + Z_5 + Z_6. \quad (1)$$

The objective function includes score parameters obtained through MCDM methods as penalty points. This encourages sourcing from the most suitable supplier based on the specified criteria. Suppliers that best meet the requirements receive a score of 1, indicating that no penalty is applied when orders are placed with them. On the other hand, suppliers are ranked relative to the best performers and receive penalties proportional to their scores. In equations (2) and (3), supplier scores used in the objective function components that account for product flow from supplier to warehouse are determined using the IFS–FUCOM–COPRAS integrated approach. After the evaluation process, the supplier that best satisfies the criteria receives a score of 1. The other suppliers are assigned values between 0 and 1 based on their performance relative to the best alternative, resulting in proportional penalties for lower performance. This structure aims to decrease the order batch size for suppliers whose performance deviates further from the desired criteria, in direct proportion to their respective scores.

$$Z_1 = \sum_{i=1}^{|I|} p_i \{ \sum_{s=1}^{|S|} \sum_{w=1}^{|W|} \sum_{t=1}^{|T|} c_{1sw} X_{swi}^t d_s (2 - scr_s)^2 \}. \quad (2)$$

The second part of the objective function focuses on the ordering costs (Z_2). Like the transportation cost component, this part includes the scores assigned to suppliers based on their adherence to traditional, social, LARG-focused, and pandemic-specific criteria (3):

$$Z_2 = \sum_{i=1}^{|I|} p_i \{ \sum_{s=1}^{|S|} \sum_{w=1}^{|W|} \sum_{t=1}^{|T|} k_s X_{swi}^t (2 - scr_s)^2 \}. \quad (3)$$

Another cost included in the objective function is the transportation cost from the warehouses to the markets, considering market demand flows (4):

$$Z_3 = \sum_{i=1}^{|I|} p_i \{ \sum_{w=1}^{|W|} \sum_{m=1}^{|M|} \sum_{t=1}^{|T|} c_{2wm} Y_{wmi}^t dem_m^t \}. \quad (4)$$

The objective function also includes the flow cost between warehouses (5):

$$Z_4 = \sum_{i=1}^{|I|} p_i \{ \sum_{a=1}^{|W|} \sum_{b=1}^{|W|} (a \neq b) \sum_{t=1}^{|T|} c_{3ab} Z_{abi}^t \}. \quad (5)$$

The objective function also considers the cost of holding inventory in warehouses (6):

$$Z_5 = \sum_{i=1}^{|I|} p_i \{ \sum_{w=1}^{|W|} \sum_{t=1}^{|T|} h_w Inv_{wi}^t \}. \quad (6)$$

The final component of the objective function is the scrap product cost accrued in the warehouses (7):

$$Z_6 = \sum_{i=1}^{|I|} p_i \{ \sum_{w=1}^{|W|} \sum_{t=1}^{|T|} sc Sal_{wi}^t \}. \quad (7)$$

Subject to

$$\sum_{w=1}^{|W|} X_{swi}^t d_s \leq cap_{si}^t; \quad \forall s \in S, i \in I, t \in T. \quad (8)$$

The constraint set (8) requires that the quantity of products drawn from each supplier to all warehouses for each scenario and each period does not exceed capacity.

Table 2. The notation table of the proposed model.

Sets		
I	The set of scenarios $I = \{i_1, \dots, I \}$	
R	The set of recycling centers $R = \{r_1, \dots, R \}$	
S	The set of suppliers $S = \{s_1, \dots, S \}$	
T	The set of time periods $T = \{t_1, \dots, T \}$	
W	The set of warehouses $W = \{w_1, \dots, W \}$	
M	The set of demand points $M = \{m_1, \dots, M \}$	
Parameters		
$c1_{sw}$	The cost of transporting one unit of product from a supplier $s \in S$ to a warehouse $w \in W$	(€/unit)
$c2_{wm}$	The cost of transporting a unit of product from a warehouse $w \in W$ to a demand point $m \in M$	(€/unit)
$c3_{ab}$	The cost of transporting one unit of product from warehouse $a \in W$ to warehouse $b \in W$	(€/unit)
h_w	The cost of holding one unit of product in the warehouse $w \in W$ for one period	(€/unit)
cap_s^i	The capacity of supplier $s \in S$ at the beginning of period $t \in T$ according to scenario $i \in I$	(unit)
dem	The demand of the market $m \in M$ at the beginning of the period at time $t \in T$	(unit)
b_w	The one-period capacity of the warehouse $w \in W$	(unit)
p_i	The probability of scenario $i \in I$	(0-1)
d_s	The order batch size of supplier $s \in S$	(pcs)
k_s	The fixed order cost for supplier $s \in S$	(€)
$shlf$	The shelf life of the product ($shlf \geq 2$)	(term)
sc_w	The penalty cost for the waste product and the cost of sending the waste product generated in the warehouse $w \in W$ to the nearest waste center for disposal or recovery	(€/unit)
h_w	The cost of holding one unit of product in the warehouse $w \in W$ for one period	(€/unit)
scr_s	Supplier score calculated for each supplier $s \in S$	(0...1)
Decision Variables		
X_{swi}^t	The number of orders placed from supplier $s \in S$ for warehouse $w \in W$ at the beginning of period $t \in T$ in scenario $i \in I$	(pcs)
Inv_{wi}^t	The amount of inventory in warehouse $w \in W$ at the end of the period at time $t \in T$ in scenario $i \in I$, beginning inventory is 0	(pcs)
Z_{abi}^t	The number of products shipped from warehouse $a \in W$ to warehouse $b \in W$ ($a \neq b$) at the beginning of the period at time $t \in T$ in the scenario $i \in I$	(pcs)
Sal_{wi}^t	The waste amount calculated at the end of period $t \in T$ according to scenario $i \in I$ at warehouse $w \in W$	(pcs)
Y_{wmi}^t	The binary variable equal to 1 if the product $I \in I$ sent from warehouse $w \in W$ to market $m \in M$ at the beginning of period $t \in T$, 0 o.t.w	(0-1)

$$\sum_{w=1}^{|W|} Y_{wmi}^t = 1; \forall m \in M, i \in I, t \in T. \quad (9)$$

The constraint set (9) to (15) consists of inventory constraints. Constraint (9) ensures that products are sent to each market from a single warehouse for each scenario and period.

The constraint set (10) tracks the inventory at the beginning of the planning horizon for each warehouse and scenario.

$$Inv_{wi}^0 = 0; \forall w \in W, i \in I. \quad (10)$$

The constraint set (11) stipulates that the inventory is held in each warehouse for each scenario and the period must not exceed the respective warehouse's capacity.

$$Inv_{wi}^t \leq b_w; \forall w \in W, i \in I, t \in T. \quad (11)$$

The constraint set (12) monitors the inventory level in each warehouse for every scenario and period. The end-of-period inventory level for each warehouse and scenario is determined by considering all product inflows and outflows and waste deductions from the inventory. The end-of-period inventory is calculated by subtracting the products sent to markets and other warehouses from the products received from all suppliers and warehouses at the beginning and then further deducting the waste products generated at the end of the period.

$$Inv_{wi}^t = \sum_{\theta=1}^t \sum_{s=1}^{|S|} X_{swi}^{\theta} d_s + \sum_{\theta=1}^t \sum_{a=1}^{|W|} Z_{awi}^{\theta} - \left(\sum_{\theta=1}^t \sum_{m=1}^{|M|} Y_{wmi}^{\theta} dem_m^{\theta} + \sum_{\theta=1}^t \sum_{b=1(b \neq w)}^{|W|} Z_{wbi}^{\theta} + \sum_{\theta=1}^t Sal_{wi}^{\theta} \right), \quad (12)$$

where $\forall w \in W, i \in I, t \in T$.

In constraint set (13), the issue of waste tracking is addressed. The occurrence of waste is contingent upon the expiration of a product within the specified period. The quantity of waste is evaluated on a case-by-case basis for each warehouse and scenario. Subsequently, inventory control is conducted retrospectively based on the shelf life, and the inflow of products

is monitored after an interval equivalent to the shelf life has elapsed. The quantity of waste is calculated by comparing the inventory with the quantities of products dispatched to warehouses and demand locations, including those destined for waste processing, and considering incoming flows from other warehouses during the relevant periods. The calculations are based on monitoring the flow of goods from each warehouse to all markets and to other warehouses. When the current time frame exceeds the product's shelf life, products stored in inventory beyond this duration become susceptible to spoilage. Equation 13 is used to determine the potential waste volume generated under these conditions. At the start of each period, order management requires a perishability evaluation for products that are not immediately aligned with demand and are intended for inventory retention. The waste generated in each period is tracked by considering inventory levels, current period demand, demand from other warehouses, and product withdrawals from other warehouses. Additionally, the total waste produced during the period is calculated by including the quantity of products previously designated for disposal.

$$Sal_{wi}^t \geq Inv_{wi}^{t-shlf+1} - \left(\sum_{\beta=t-shlf+2}^t \sum_{m=1}^{|M|} Y_{wmi}^{\beta} dem_m^{\beta} + \sum_{\beta=t-shlf+2}^t \sum_{b=1(b \neq w)}^{|W|} Z_{wbi}^{\beta} + \sum_{\beta=t-shlf+2}^{t-1} Sal_{wi}^{\beta} \right) + \sum_{\beta=t-shlf+2}^t \sum_{a=1(a \neq w)}^{|W|} Z_{awi}^{\beta}, \quad (13)$$

where $\forall w \in W, i \in I, t \in (1..|T|: t \geq shlf)$. The constraint set (14) encompasses the tracking of periods devoid of scrap generation. If the examined time interval is not exceeded by the product's shelf life, the amount of waste generated during this period is deemed to be zero.

$$Sal_{wi}^t = 0; \forall w \in W, i \in I, t \in (1..|T|: t < shlf) \quad (14)$$

Constraint set (15) pertains to the scenario in which inventory is transferred between warehouses. It assesses the situation in which inventory from one warehouse is received to fulfill the demand at another. The constraint guarantees that if the

incoming inventory is less than the demand, it is accurately considered.

$$\sum_{a=1}^{|W|} Z_{awi}^t \leq \sum_{m=1}^{|M|} Y_{wmi}^t dem_m^t, \quad (15)$$

where $\forall w \in W, i \in I$, and $t \in T$. Constraint sets (16) to (20) define the variables used in the model.

$$X_{swi}^t b \in Z^+ \cup 0; \quad \forall s \in S, w \in W, i \in I, t \in T \quad (16)$$

$$Y_{wmi}^t \in \{0,1\}; \quad \forall w \in W, m \in M, i \in I, t \in T \quad (17)$$

$$Z_{abi}^t \in Z^+ \cup 0; \quad \forall a \in W, b \in W (a \neq b), i \in I, t \in T \quad (18)$$

$$Inv_{wi}^t \in Z^+ \cup 0; \quad \forall w \in W, i \in I, t \in T \quad (19)$$

$$Sal_{wi}^t \in Z^+ \cup 0; \quad \forall w \in W, m \in M, t \in T \quad (20)$$

D. Determining supplier scores: The intuitionistic fuzzy set theory and multi-criteria decision-making

This section presents the methodology for determining supplier scores, with a particular focus on the application of IFS and MCDM approaches. The section explains the process used to derive the supplier score parameters (scr_s) for the proposed mathematical model, highlighting the critical role of evaluating suppliers based on key criteria and aligning product and service flows accordingly.

A series of steps were followed to determine the supplier score parameter. Initially, a comprehensive literature review was conducted to establish supplier selection criteria by examining studies that address the uncertainties introduced by the COVID-19 process within supply chain risk assessment. A systematic search was performed in the Web of Science and Science Direct databases using the keywords "supplier selection," "vendor selection," and "procurement" in conjunction with "covid" and "pandemic." The results of this search were evaluated, leading to the identification of the main and sub-criteria presented in Appendix-A. Based on the literature review, supplier selection criteria were examined from different perspectives: traditional, social, LARG, and pandemic-specific. Experts determined the relative importance of these criteria using the IFS FUCOM methodology. The procurement manager's evaluations of current suppliers were then analyzed using the COPRAS method with the established criteria weights. This process resulted in a supplier score parameter, which was then integrated into the optimization problem.

The study proposes applying to the IFS to evaluate criteria involving multiple decision-makers. This approach allows us to analyze the impact of the identified criteria on supplier selection and determine their respective importance levels. To determine the criteria's importance levels, we are using FUCOM, a relatively new approach based on optimization in assigning weights. By integrating IFS and FUCOM, we can thoroughly assess each criterion for every decision-maker. This allows us to confidently determine the final importance levels of the criteria in the supplier evaluation phase. MCDM methodologies offer a highly versatile and pragmatic framework for conducting complex multidimensional evaluations. Several factors justify the selection of this method combination. According to the mathematical model's configuration, the supplier that best meets the specified criteria receives a score of 1. Within this context, the COPRAS method is an appropriate tool for determining final supplier performance. In COPRAS, the top alternative is assigned a value of 1, representing the maximum possible score, while other alternatives receive values between 0 and 1 based on their distance from the optimal solution. This scoring system indicates each supplier's relative proximity to the optimal choice. Such a configuration encourages the objective function to allocate a larger share of product procurement to the most effective

supplier, while also compensating other suppliers in proportion to their performance scores. Although alternative methods could be developed, doing so would require revising the penalty or reward components in the objective function that depend on supplier scores.

Additionally, the IFS approach addresses uncertainties that may arise during the evaluation process, enabling the integration of expert opinions while explicitly accounting for them. The FUCOM method, selected for criteria weighting, is an optimization-based technique that aligns with the study's methodological framework. When numerous criteria require evaluation, FUCOM has been shown to reduce complexity for evaluators and to facilitate straightforward ranking of criteria by significance. This methodological choice is consistent with the overall study design. Moreover, the proposed methods offer user-friendliness and reduce the computational burden on decision-makers. All calculations can be conducted in Excel without specialized solvers, further supporting the adoption of the proposed evaluation model.

1. The intuitionistic fuzzy set theory (IFS) in determining expert weights

The COVID-19 pandemic has introduced a considerable degree of uncertainty into this study. It is difficult to quantify the issues that arise in the selection and evaluation of suppliers. To address this issue, it is possible to seek guidance from expert opinions by utilizing linguistic expressions [36]. In this context, IFS is a tool for assessing decision-makers based on qualitative expressions, thereby enhancing the decision-making process in intricate or uncertain scenarios. IFS can offer significant assistance in developing hierarchical structures in MCDM methodologies, particularly in situations involving multiple decision-makers.

In the IFS introduced by Atanassov in 1986, each element (u) is associated with membership (μ), non-membership (ν), and hesitation indices (π) [37]. These indices are defined as follows: For a finite universal set $u \in U$, defined within a finite universal set u , the theory can be expressed using the following equations (21)-(26) [38]-[40]:

$$A = \{(u, \mu_u, \nu_u) \mid u \in U\}, \quad (21)$$

$$0 \leq \mu_u + \nu_u \leq 1, \forall u \in U, \quad (22)$$

$$u \in U \rightarrow \mu_u \in [0,1] \text{ and } \nu_u \in [0,1], \quad (23)$$

where μ_u denotes the membership degree of the element $u \in U$ in the fuzzy set A ; ν_u represents the non-membership degree of the element $u \in U$ in the fuzzy set A ; π_u is the hesitation index, reflecting the degree of uncertainty or indecision about the membership of $u \in U$ in the fuzzy set A .

In IFS, the membership degree functions are strictly governed by the conditions defined in equations (23) and (24). As shown in equation (24), IFS extends fuzzy sets by introducing the hesitation index (π_u). The hesitation index reflects the situation where there is insufficient information about the element $u \in U$. A reduction in the hesitation index indicates a decrease in uncertainty. A value of zero represents the absence of uncertainty. The hesitation index function is defined by (24):

$$\pi_u = 1 - \mu_u - \nu_u, \forall u \in U \quad (24)$$

In the context of IFS being employed to assign importance weights to decision-makers, equations (25) and (26) typically follow the following stages [41]. In assigning importance to decision-makers, linguistic expressions are assigned based on their significance, and $D_u = [\mu_u, \nu_u, \pi_u]$, presents the intuitionistic fuzzy numbers (IFNs) for evaluating the decision-makers. The weight of decision-maker u , denoted as λ_u , is calculated based on the number of decision-makers $|U|$ and the IFNs $D_u = [\mu_u, \nu_u, \pi_u]$ assigned according to the ranking of

decision-makers (u). The decision-maker importance weights are computed as following equations (25), (26) [35], [42]:

$$\lambda_u = \frac{[\mu_u + \pi_u(\frac{\mu_u - \nu_u}{\mu_u + \nu_u})]}{\sum_{a=1}^{|U|} [\mu_a + \pi_a(\frac{\mu_a - \nu_a}{\mu_a + \nu_a})]}, \forall u \in U \quad (25)$$

$$\lambda_u \in [0,1] \quad \forall u \in U \quad \text{and} \quad \sum_{u=1}^{|U|} \lambda_u = 1. \quad (26)$$

2. The full consistency method (FUCOM) for criteria weighting

The ranking and weighting of criteria in MCDM has been the focus of many studies [43]. In this study, the FUCOM, a subjective weighting method, is employed to assign weights to the criteria. The mathematical model is constructed by three fundamental steps for criteria that are subject to comparison within a specific hierarchy. The solution to the linear programming model provides the optimal values of the criteria weights and the degree of deviation from full consistency [44]. The FUCOM method employs a ranking process to determine the relative importance of the criteria, thereby deriving the weights for each. This process involves a comparative and contrasting analysis of the criteria, which ultimately results in the determination of their respective weights [45]. A notable benefit of this approach is its minimal demand for pairwise comparisons, which streamlines the assessment of expert proficiency [46]. In methods with similar objectives that involve pairwise comparisons, such as BWM (Best-Worst Method), AHP (Analytic Hierarchy Process), and DEMATEL (Decision-Making Trial and Evaluation Laboratory), the number of comparisons increases exponentially with the number of criteria, posing challenges for decision-makers. In contrast, the FUCOM method requires only $(n - 1)$ pairwise comparisons for a problem with (n) criteria, making it more manageable for decision-makers [47].

Step 1: Experts determine the ranking of criteria based on their preferences for the criteria's importance as expressed in (27):

$$C_{j(1)} \gg C_{j(2)} \gg \dots \gg C_{j(k)}, \quad (27)$$

where $\forall (j, k) \in (1, 2, \dots, n)$.

Step 2: For n criteria, the comparative superiority values of the ranked criteria are found by $n - 1$ comparisons, as shown in (28):

$$\varphi = \left[\varphi_{\frac{1}{2}}, \varphi_{\frac{2}{3}}, \varphi_{\frac{3}{4}}, \dots, \varphi_{\frac{k-1}{k}} \right], \forall k \in (1, 2, \dots, n). \quad (28)$$

Step 3: The objective function that minimizes the deviation from full consistency (29) and the constraint set (30)–(33) are formulated.

Objective function,

$$Z_{min} = X. \quad (29)$$

Subject to:

Following the hierarchical superiority values among criteria, the comparative superiority values between criteria are calculated as given in (30):

$$\left| \frac{w_{j-1}}{w_j} - \varphi_{\frac{k-1}{k}} \right| \leq X, \forall j \in (2, \dots, n), k = j. \quad (30)$$

The transitivity condition is formulated as in (31):

$$\left| \frac{w_{j-2}}{w_j} - \left(\varphi_{\frac{k-2}{k-1}} \right) \left(\varphi_{\frac{k-1}{k}} \right) \right| \leq X, \forall j \in (3, \dots, n). \quad (31)$$

The sum of the weight values is equated to 1, as shown in (32):

$$\sum_{j=1}^n w_j = 1. \quad (32)$$

The non-negativity constraint for the optimization model is specified in (33):

$$w_j \geq 0, \forall j \in (1, 2, \dots, n) \quad (33)$$

The optimization model minimizes the deviation from complete consistency. The solution to the optimization model provides the criteria weights that minimize deviation from full consistency.

3. The complex proportional/relative assessment (COPRAS) for supplier evaluation

The decision-making process is complex and challenging due to the sheer volume of data and factors involved. Those charged with decision-making frequently find themselves compelled to make complex choices about the allocation of public funds within a constrained budget, with a limited number of interventions to prioritize. Multi-criteria decision-making techniques have been identified as a potentially beneficial instrument to help decision-making in such contexts [48]. COPRAS, which assesses the relative importance and benefit degrees of alternatives, was first offered to the literature in 1994 [49]. The method proportionally assesses the degree of benefit of alternative performance values. Ultimately, it allows for determining the similarity percentage of a decision alternative compared to the ideal alternative.

COPRAS offers a user-friendly structure for evaluating quantitative and qualitative factors. It assesses decision alternatives based on their benefit/cost orientation, using the highest and lowest values for evaluation. The method enables decision-makers to rank alternatives based on performance. The technique is described in (34)–(44) [50]–[53].

Step 1: Construct the decision matrix. In equation (34), the decision matrix $([X_{ij}]_{m \times n})$ is structured such that the rows represent the decision alternatives to be ranked (m alternatives), and the columns represent the evaluation factors (for n criteria).

$$[X_{ij}]_{m \times n} = \begin{bmatrix} x_{11} & \dots & x_{1n} \\ \vdots & \dots & \vdots \\ x_{m1} & \dots & x_{mn} \end{bmatrix} \quad (34)$$

Step 2: Normalize the decision matrix. Equations (35)–(37) eliminate problems arising from different scales and units of measurement, and the decision matrix is normalized. The sum of the normalized performance values for all alternatives equals one.

$$\bar{X}_{ij} = \begin{bmatrix} \bar{x}_{ij} & \dots & \bar{x}_{1n} \\ \dots & \dots & \dots \\ \bar{x}_{m1} & \dots & \bar{x}_{mn} \end{bmatrix}, \forall i \in (1, 2, \dots, m), j \in (1, 2, \dots, n) \quad (35)$$

$$\bar{x}_{ij} = \frac{x_{ij}}{\sum_{s=1}^m x_{sj}}, \forall (i, j) \in (1, 2, \dots, n) \quad (36)$$

$$\sum_{i=1}^m \bar{x}_{ij} = 1, \forall j \in (1, 2, \dots, n) \quad (37)$$

Step 3: Construct the weighted normalized matrix. The relative importance of the criteria in question varies when evaluating alternatives. As a result, the criteria themselves are assigned weights based on their respective importance. The weighted normalized performance values are obtained by applying (38) and (39).

$$\hat{X}_{ij} = \bar{X}_{ij} w_j, \forall i \in (1, 2, \dots, m), j \in (1, 2, \dots, n), \quad (38)$$

$$\sum_{i=1}^m \hat{x}_{ij} = 1, \forall j \in (1, 2, \dots, n), \quad (39)$$

$$\sum_{i=1}^m \sum_{j=1}^n \bar{X}_{ij} = 1. \quad (40)$$

As illustrated in (40), the total weighted performance values for all alternatives and criteria sum up to one.

Step 4: Calculate the benefit and cost-oriented total weighted normalized values. At this stage, the alternatives are evaluated based on their benefit-maximization and cost-minimization properties:

- K_{maks} : The set of criteria aimed at maximization, denoted as $K_{maks} = \{1, 2, \dots, |K_{maks}|\}$.

- K_{min} : The set of criteria aimed at minimization, denoted as $K_{min} = \{1, 2, \dots, |K_{min}|\}$.
- The benefit-side total weighted normalized values (S_{+i}) are defined as follows: The alternatives are evaluated according to their performance-maximizing benefits, as outlined in (41).
- Cost-side total weighted normalized values (S_{-i}): Alternatives are evaluated according to their capacity to reduce costs, as outlined in (42):

$$S_{+i} = \sum_{j \in K_{maks}} \bar{X}_{+ij}, \forall i \in (1, 2, \dots, |K_{maks}|), \quad (41)$$

$$S_{-i} = \sum_{j \in K_{min}} \bar{X}_{-ij}, \forall i \in (1, 2, \dots, |K_{min}|). \quad (42)$$

Step 5: Calculate the performance index values. The performance index values (Q_i) for each decision alternative is calculated using the total benefit and cost-oriented values, as in (43):

$$Q_i = S_{+i} + \frac{S_{-min} * \sum_{c=1}^m S_{-c}}{S_{-c} * \sum_{c=1}^m (\frac{S_{-min}}{S_{-c}})}, \forall i \in (1, 2, \dots, m). \quad (43)$$

Step 6: Calculate the relative importance of alternatives. The relative importance weight (P_i) is calculated such that the ideal alternative has a value of 100%. Other alternatives receive values between 0% and 100%, as described in (44):

$$P_i = \left[\frac{Q_i}{Q_{maks}} \right] * \%100, \forall i \in (1, 2, \dots, m). \quad (44)$$

Step 7: Evaluate alternatives and determine the preference ranking. The relative importance values (P_i) calculated in the preceding step are arranged in descending order, thereby generating the preference ranking of the alternatives. The IFS-FUCOM-COPRAS methods used to identify and evaluate alternatives, decision criteria and decision makers provide supplier ratings, which are then used as a parameter in the proposed mathematical model.

E. Numerical analysis

This section presents a case study and findings to demonstrate the applicability of the developed closed-loop supply chain network design problem model. A case study was conducted to verify the method's applicability in a real-world context. This section introduces the dataset used in the mathematical model, followed by the supplier evaluation methods using IFS and MCDM to generate the supplier score parameter. The section continues with the research results and discussion. The problem was solved using the academic version of IBM ILOG CPLEX 20.1.0 on a computer with an Intel (R) Core (TM) i7-10510U CPU @ 1.80GHz 2.30 GHz processor, a 64-bit operating system, and 16.0GB RAM.

1. Introduction of the dataset for the case study

The case study focuses on procuring medical supplies for a hospital in Türkiye's healthcare sector. This research examines a real-world case involving a hospital network to illustrate the practical applicability of the proposed framework. The analysis focuses on a product group characterized by perishability. Expert evaluations were conducted with hospital staff directly involved in procurement and operational processes. These staff members evaluated both product and supplier-related criteria. The data set used in the model includes both real and derived parameters. Real data, such as hospital locations and network structures, were obtained from public sources or directly from participating hospitals. Due to concerns about competitiveness and confidentiality, some operational parameters could not be provided by the organizations. In these cases, parameter values were determined using two complementary approaches. First, values were estimated based on realistic assumptions informed by operational observations, such as estimated fuel cost per kilometer. Second, if widely accepted benchmark values existed in the literature, those values were adopted from prior studies, such as hourly driver wages. This methodological approach ensures that the case study maintains practical realism and

methodological transparency while addressing common data availability challenges in real-world supply chain research.

The case involves four suppliers (S) two central warehouses (W), ten demand points/hospitals (C), and two recycling centers (R). The locations of the network's nodes were obtained from Google MyMaps and are shown in Fig. 2.

In generating transportation cost data, fuel consumption and the price per liter of diesel fuel were considered. A single vehicle type was utilized, with an average fuel consumption of 25 liters per 100 km. The driver's remuneration was established at a fixed rate of 6 € per hour. It was assumed that the vehicle's average speed would be 80 km/h.

The distance data was obtained from Google Maps as the shortest distances. These distances were used to calculate transportation costs in network design. The problem examines 12 months.

The generated transportation cost data considering fuel consumption and driver fees [54]. The vehicle used is a standard type, specifically a MAN TGS model, with an average fuel consumption of 25 liters per 100 kilometers. The price of diesel fuel is fixed at €2 per liter, and the driver's fee is set at €6 per hour. Demand data were obtained through expert opinions and generalized for consideration.

Due to uncertainties in raw material procurement caused by supply fluctuations, the problem is considered high, medium, and low-capacity scenarios. Scenario 1 represents high supplier capacity, Scenario 2 represents medium supplier capacity, and Scenario 3 represents low supplier capacity. In the scenarios, a high supply condition is assumed and subsequently reduced by 20% to define the second and third scenarios.

In this problem, supplier scores were calculated and incorporated using the IFS-FUCOM-COPRAS methods. To inform the calculations, a review of the relevant literature was conducted to examine studies on supplier selection during the pandemic. In addition, the evaluation criteria for suppliers were identified. The criteria for supplier evaluation can be grouped into four main categories: traditional, social, LARG-focused, and pandemic-specific. Given that pandemic-specific conditions require periodic evaluations beyond the company's control, it is also necessary to assess the company's administrative management. Organizations are also affected by the social and environmental conditions in which they operate and by the risk-monitoring policies of administrative authorities.

2. Determining expert weights using intuitionistic fuzzy set (IFS) theory

This section of the study presents an application in which decision-makers are evaluated in the context of the medical product purchasing process, using the IFS methodology. Table 3 presents the IFNs corresponding to the linguistic expressions assigned during the evaluation of decision-makers using IFS.

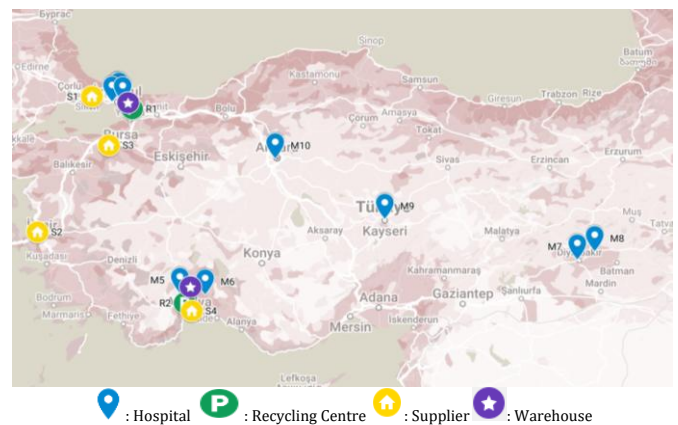


Figure 2. Layout of closed-loop supply chain actors [35].

Table 3. Representation of linguistic fuzzy number [42].

Linguistic Term	IFN
Very Important (AI)	(0.80-0.10)
Important (VI)	(0.50-0.20)
Moderate (FI)	(0.50-0.50)
Poor (LI)	(0.30-0.50)
Very Poor (EI)	(0.20-0.70)

The selection criteria determined through literature review and expert opinions were evaluated by a purchasing manager in the healthcare sector, a surgical and sterilization clinic trainer, and an academic with experience in supplier selection, as shown in Table 4. The research indicates that the contribution of three experts is deemed sufficient in the decision-making process according to literature [21]. MCDM processes emphasize the use of expert knowledge relevant to the specific problem, rather than relying on large-sample survey studies focused on statistical generalizability. The detailed information provided by a small group of subject-matter experts reduces cognitive noise in data set, in contrast to the increased variance associated with large, randomly chosen samples. In these approaches, the consistency of expert judgments, which reflects internal validity, is more critical than sample size. A mathematically validated, consistent view provides sufficient support for the model's reliability. Furthermore, increasing the number of experts may hinder consensus-building and complicate the decision-making process. The aim of MCDM is to optimize cognitive load and enable high-precision outcomes with a limited number of experts. Calculating the relative importance of expert evaluations is intended to streamline and enhance the supplier selection process.

The importance levels of the experts are determined as in Table 4. The importance levels assigned are very important for the purchasing manager, important for the academician, and medium for the operating room and sterilization clinic trainer. This classification is based on the experts' direct or indirect involvement in the supplier selection decision-making process, as well as their experience. Subsequently, the expert importance calculated using the IFS method is given in Table 5, using (25).

In the subsequent phase of the study, each expert assesses the supplier selection criteria based on their professional expertise, using the FUCOM method. The criteria are calculated using Intuitionistic Fuzzy Sets (IFS) and integrated with FUCOM to refine each criterion's weighting. The IFS weights thus capture the influence of expert judgments on the final decision, thereby enhancing the robustness of the criteria-evaluation process.

3. Determining criteria weights using IFS-FUCOM integration

This section outlines the implementation of the FUCOM approach to determine the importance rankings of traditional, social, LARG-focused, and pandemic-specific criteria. These rankings are presented in two ways: first, in isolation within each category; and second, in comparison across categories. The approach is grounded in expert evaluations. Each expert was tasked with ranking the supplier selection criteria by their level of significance, indicating whether each criterion was of greater importance (using the symbol >>) or of equal importance (=).

To determine the relative importance of the criteria, the weights were calculated using FUCOM. These weights were then adjusted for accuracy using Intuitionistic Fuzzy Sets (IFS), and finally, the expert-specific weightings were incorporated. The global weights

Table 4. Expert evaluations and criteria.

Expert	Importance Degree	Sector	Experience (Years)	Position
U_1	Very Important	Healthcare	15	Purchasing Manager
U_2	Medium	Healthcare	10	Operating Room and Sterilization Clinic Trainer
U_3	Important	Education	17	Academic

Table 5. Importance of decision-making experts.

Expert	IFS Score	Expert	IFS Score	Expert	IFS Score
U_1	0.42264	U_2	0.23774	U_3	0.33962

were obtained by multiplying each primary criterion's weight by its sub-criterion's weights, with final adjustments based on the expert weightings via IFS. As shown in Fig. 3, the final sub-criteria weights indicate cost (0.18), social factors (0.13), and quality (0.10) serve as the pivotal determinants in the supplier selection process, collectively representing approximately 40% of the cumulative weight. In stark contrast, environmental and strategic dimensions, specifically green perspective and visibility, emerge as the least significant factors, each contributing a marginal share of roughly 1% to the overall evaluation framework.

Looking at the final weights of the criteria in Table 6, traditional and social criteria have a more significant impact on decisions during the pandemic, while LARG-focused criteria are comparatively less considered. This situation is interpreted because of operating under extraordinary environmental conditions such as a pandemic. Organizations tend to prioritize the continuity of their operations when making decisions under risk conditions, potentially overriding long-term considerations. Because the product is a health kit, evaluators may have assigned lower importance to criteria such as green competencies.

4. Application of the IFS-FUCOM integrated COPRAS for supplier scoring

The synergistic application of IFS, FUCOM, and COPRAS represents a potent methodology, ensuring consistent and reliable results in the supplier selection process. Subsequently, the calculation of expert weights and integration of criterion scores, conducted using IFS and FUCOM, facilitate the comparison of suppliers. This section outlines the application of the COPRAS method, building on the methodology presented in previous sections.

Step 1: In the supplier selection problem with 4 alternatives and 19 criteria, the performance value x_{ij} represents the performance of alternative $i = \{S_1, S_2, S_3, S_4\}$ against criterion $j = \{1, 2, \dots, 19\}$. The initial decision matrix is the first step in the process. The initial decision matrix for all alternatives and criteria is presented in Table 6.

The evaluation of alternatives and the determination of preference rankings are outlined in this section. The preference rankings are presented in Table 7. According to the results, among the four suppliers evaluated based on traditional, social, LARG-focused, and pandemic-specific criteria, Supplier 1 (S_1) is found to be the most suitable. Supplier 2 (S_2) ranks second in terms of suitability compared to Supplier 1, while Supplier 4 (S_4) has the least favorable scores relative to the best performing supplier.

The overall scores of the suppliers are closely aligned, indicating that all four suppliers comply with the specified criteria. The model suggests that there are no situations where the supplier would need to be excluded from the supply chain network due to non-compliance with the criteria.

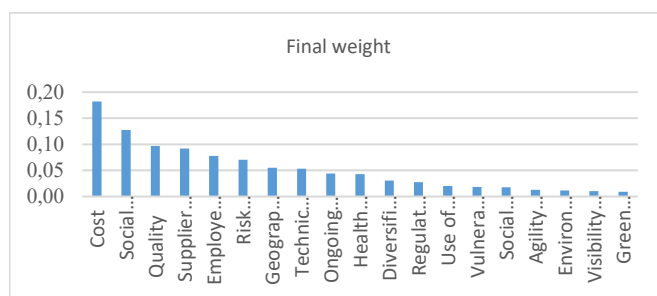


Figure 3. Comprehensive criteria importance rankings.

Table 6. Performance scores of each supplier alternative for the given criteria.

	C_{11}	C_{12}	C_{13}	C_{14}	C_{21}	C_{22}	C_{23}	C_{31}	C_{32}	C_{33}	C_{34}	C_{35}	C_{36}	C_{37}	C_{38}	C_{41}	C_{42}	C_{43}	C_{44}
S_1	6.45	6	6	1	6	1	8	7	6	6	8	7	6	1	1	1	1	1	8
S_2	7.65	6	5	3	6	1	6	7	6	6	7	7	6	1	1	1	1	1	8
S_3	8.25	7	6	2	6	1	6	7	6	6	7	7	6	1	1	1	1	1	8
S_4	9.00	6	6	2	6	1	7	7	6	6	6	7	6	1	1	1	1	1	8

Table 7. Preference ranking.

Rankings	Supplier	P_i	P_i
1	Supplier 1 (S_1)	100.00	1
2	Supplier 2 (S_2)	98.14	0.9814
3	Supplier 3 (S_3)	96.85	0.9685
4	Supplier 4 (S_4)	95.04	0.9504

By integrating IFS, FUCOM, and COPRAS methods, we have devised a systematic approach to incorporate expert evaluations to derive sustainability scores for existing suppliers. The supplier scores serve as pivotal elements within the objective function of the proposed mathematical model, reflecting adherence to conventional criteria in addition to social, LARG-focused, and pandemic-specific considerations, as evaluated by three experts with diverse backgrounds.

A score of one for a supplier indicates a high level of compliance with the established criteria, thereby implying that selecting this supplier incurs no penalties within the objective function. Conversely, suppliers are subject to penalties based on their scores relative to the most suitable supplier, thereby facilitating the optimization of product flows while accounting for these penalty assessments. This methodology allows for a comprehensive evaluation of two critical factors for businesses: cost and sustainability. This is demonstrated by the proposed mathematical model.

5. Solution of the mathematical model and evaluation of results

Using the introduced dataset, an optimal solution for a perishable product was obtained based on traditional, social, LARG-focused, and pandemic-specific criteria. The mathematical model, which penalizes low-scoring suppliers and aims to minimize costs, achieved optimal solutions in approximately three minutes. The key performance metrics of the solution are presented in Table 8. The total cost for the solution is €13,991. Of this total, approximately 71% is attributed to transportation costs from the warehouse to hospitals, while about 24% is associated with transportation costs from suppliers to the warehouse.

The example flow diagram presented in Fig. 4 illustrates the flows occurring over time in each scenario. In the case of scenario 1, which represents high capacity, the flow of goods from supplier S_1 to warehouse W_1 is shown. Each shipment consists of 800 units of product. For warehouse W_1 located in Istanbul, the optimal procurement involves receiving four shipments from supplier S_1 . At the beginning of the first period, the total quantity of products arriving from suppliers is 3200 units. Out of these 3200 units, 125 units are sent to meet the period's needs for warehouse W_2 . The total demand of the four hospitals located in Istanbul during the first period is 2550 units, which is fulfilled from this warehouse. At the end of the period, the remaining inventory in the warehouse amounts to 525 units.

Table 9 provides a comprehensive illustration of the product flows between nodes. This table illustrates the quantities of

Table 8. Key performance indicators.

Key performance indicators	Cost (€)
Inventory holding cost	412.85
Waste cost	78.80
Ordering cost	65.77
Transportation cost from supplier to warehouse	3428.70
Transportation cost from warehouse to hospitals	9867.40
Inter-warehouse transportation cost	137.52
Total cost	13991

products flowing into the two warehouses W_1 and (W_2) and from the warehouses to the demand points (hospitals) over the 12 periods considered in the problem. Furthermore, the table provides detailed information on the quantities of expired products sent to recycling centers.

From an examination of Table 9, it is evident that the total amount of products entering the warehouse comprises those received from suppliers, products transferred from other warehouses, and the inventory carried over from the previous period. Conversely, the total amount of products existing in the warehouse includes those sent to demand points and those sent to recycling centers as waste. The difference between the products entering and exiting the warehouse provides the inventory amount for the respective period, which aligns with the inventory levels obtained from the model solution.

F. Sensitivity analysis

In this section, an array of analytical techniques was employed to examine the data pertinent to the problem, and the solutions of the developed mathematical model were evaluated across a range of scenarios. The objective of these scenarios is to ascertain the influence of selected parameters on the results. The scenarios are designed not only to demonstrate the model's applicability in a real-world context but also to examine the impact of parameter changes on the outcomes.

During the scenario analysis, three parameters of particular significance to the network design were examined: supplier score, supplier capacity, and product shelf life. The impact of varying these parameters was investigated while maintaining consistency in other pertinent data. The results obtained by applying different values to each parameter were analyzed and interpreted.

1. Impact of supplier scores

A series of solutions were obtained by inputting different values to examine the impact of variations in supplier scores on the

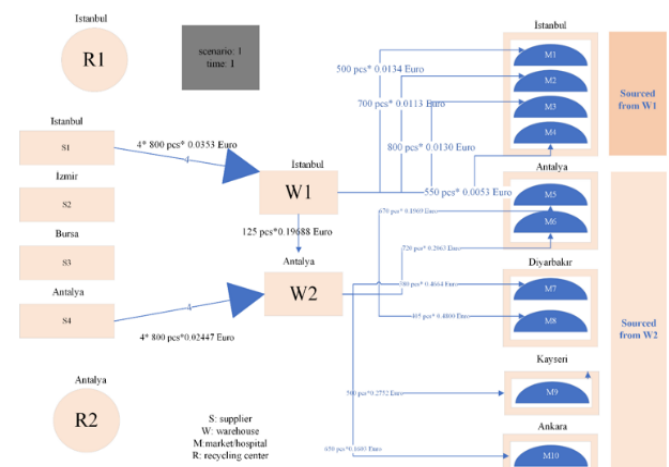


Figure 4. A sample flow diagram [35].

Table 9. Inventory tracking for warehouse 1 and (warehouse 2).

Time period	1	2	3	4	5	6	7	8	9	10	11	12
Initial inventory from suppliers	3200 (3200)	2400 (2400)	3200 (2400)	3200 (3200)	8000 (3200)	4800 (3200)	5600 (3200)	8000 (3200)	3200 (3200)	2400 (2400)	3200 (2400)	3200 (2400)
Initial inventory from warehouse	0 (125)	0 (0)	0 (0)	0 (0)	0 (70)	0 (375)	0 (285)	0 (380)	0 (35)	0 (0)	0 (50)	0 (85)
Previous period inventory	0 (0)	525 (0)	0 (0)	0 (0)	0 (0)	175 (0)	0 (0)	285 (0)	0 (0)	450 (0)	0 (0)	385 (0)
Initial customer demand	2550 (3325)	2850 (2325)	3200 (2075)	3150 (2925)	7605 (3270)	4600 (3575)	5000 (3485)	7905 (3580)	2550 (3235)	2850 (2235)	2735 (2450)	3500 (2485)
Products sent to warehouse	125 (0)	0 (0)	0 (0)	0 (0)	70 (0)	375 (0)	285 (0)	380 (0)	35 (0)	0 (0)	50 (0)	85 (0)
Waste	0 (0)	75 (75)	0 (325)	50 (275)	150 (0)	0 (0)	30 (0)	0 (0)	165 (0)	0 (165)	30 (0)	0 (0)
Inventory level	525 (0)	0 (0)	0 (0)	0 (0)	175 (0)	0 (0)	285 (0)	0 (0)	450 (0)	0 (0)	385 (0)	0 (0)

Values in parenthesis are related to the 'warehouse 2'.

fundamental performance values of the presented mathematical model. The effects of parameter variations on performance values are detailed in Table 10.

As illustrated in Table 11, the implementation of the revised scoring system has reduced the cost of transportation from the supplier to the warehouse. Conversely, the holding cost at the warehouse, transportation cost to hospitals, and inter-warehouse transportation cost increase, resulting in an overall increase in total cost.

A more comprehensive examination of weighting sensitivity would certainly be beneficial; however, the inherent reliance of the FUCOM method on the magnitude ranking between criteria precluded the possibility of experts expressing and evaluating this using a different method.

2. Effects of supplier capacities

This stage of the analysis assesses the model's sensitivity to variations in capacity data by systematically examining three scenarios: high, medium, and low capacity. The aim is to provide a comparative analysis of the high-capacity scenarios relative to the medium- and low-capacity scenarios. To facilitate the comparison, the model is structured with specific capacity assumptions. The capacity for the scenarios under consideration is set to 1, while the capacity for other scenarios is set to 0. As shown in Table 12, in the high-capacity scenario, warehouse holding costs are considerably reduced due to continuous, sufficient product supply from suppliers.

In the absence of supply constraints, the necessity to maintain inventory for future periods is reduced. Conversely, within the low-capacity framework, the cost of inventory storage escalates due to the necessity of maintaining inventory levels to meet future demand, despite constraints imposed by supplier capacity.

Waste generation also differs between the scenarios, with higher levels observed in the high-capacity scenario and lower levels in the low-capacity scenario. This discrepancy can be attributed to product availability being closely aligned with demand under low-capacity conditions, reducing the accumulation of excess inventory and the generation of waste. In addition, the cost of transporting goods between warehouses is higher in the low-capacity scenario. This is because any unmet supply demand must be met by alternative sources in other warehouses.

In general, total costs are higher in low supplier capacity scenarios. Total costs are 6.3% lower than proportional costs

Table 10. Parameter variations for the impact of supplier scores.

Supplier	Supplier score in the base case	Supplier score in new scenario
S1	1.0000	1.00
S2	0.9814	0.80
S3	0.9685	0.95
S4	0.9504	0.60

when only high-capacity scenarios are implemented. Conversely, when only low-capacity assumptions are used, total costs increase by 8.3% compared to proportional costs.

3. Impact of shelf life

The product under consideration is perishable, and this section of the study aims to assess how changes in the shelf-life parameter, blended into the model as a measure of perishability, affect the model's solution. Specifically, the impact of varying shelf-life durations on key performance metrics is analyzed.

As shown in Table 13, extending the shelf-life parameter from two to three periods leads to a 0.606% increase in inventory holding costs. This increase is attributed to the product being stored in the warehouse longer than it would have been sent to the waste center, thus reducing waste costs. In this case, transportation costs remain relatively unchanged, while inter-warehouse flow expenses slightly decrease.

Changes in waste separation resulting from an extended shelf life can lead to variations in supplier order quantities and product flows between depots. In summary, changes in the shelf-life parameter not only affect the amount of waste generated but also alter supplier order quantities and product flows between warehouses, with a significant impact on overall supply chain performance.

III. MANAGERIAL IMPACT

The proposed framework aims to improve the quality of managerial decision-making under uncertainty by incorporating intuitionistic fuzzy sets into expert evaluations. Supplier assessment frequently involves qualitative criteria such as supplier reputation, responsiveness, and health threat where judgments may be hesitant or ambiguous. By capturing these uncertainties, the approach produces more realistic and robust evaluation outcomes.

The model serves as a comprehensive, practical decision-support tool, enhancing supplier selection, procurement planning, and

Table 11. Key performance indicators for base case and scenario 1.

Key performance indicators	Base case	Scenario 1	The percentage variation (%)
Inventory holding cost (€)	412.85	465.95	+12.862
Waste cost (€)	78.80	46.825	-40.577
Ordering cost (€)	65.77	65.75	-0.030
Transportation cost from supplier to warehouse (€)	3428.7	3339.3	-2.607
Transportation cost from warehouse to hospitals (€)	9867.4	9959.7	+0.935
Inter-warehouse transportation cost (€)	137.52	149.33	+8.588
Total cost (€)	13991	14027	+0.257

*In the scenario where solutions are obtained with the new supplier scores, the warehouse holding cost has increased by 12.86%.

Table 12. Key performance indicators for different capacity utilization.

Key performance indicators	Base case	High-capacity assumption	Medium capacity assumption	Low-capacity assumption
Inventory holding cost (€)	412.85	182.00	285.50	733.00
Waste cost (€)	78.80	109.00	93.75	33.75
Ordering cost (€)	65.77	65.50	65.50	66.40
Transportation cost from supplier to warehouse (€)	3428.70	2734.30	3256.40	4179.00
Transportation cost from warehouse to hospitals (€)	9867.40	9737.80	9852.80	9944.80
Inter-warehouse transportation cost (€)	137.52	276.61	93.516	197.86
Total cost (€)	13991.00	13105.00	13647.00	15155.00
Percentage change in cost (%)	0.00	-6.3*	-2.5	+8.3
Probabilities of Scenario Realization	$p_1 = 0.2$ $p_2 = 0.5$ $p_3 = 0.3$	$p_1 = 1$ $p_2 = 0$ $p_3 = 0$	$p_1 = 0$ $p_2 = 1$ $p_3 = 0$	$p_1 = 0$ $p_2 = 0$ $p_3 = 1$

* Under the high-capacity assumption, the solution obtained shows a decrease of 6.3% compared to the base case.

Table 13. Key performance indicators for variations in shelf-life parameters.

Key performance indicators	Shelf life: 2	Shelf life: 3	The percentage variation	Shelf life: 12	The percentage variation (%)
Inventory holding cost (€)	412.85	415.35	+0.606%*	628.5	+52,23
Waste cost (€)	78.80	78.35	-0.571%	30.65	-61,10
Ordering cost (€)	65.77	65.77	0.000%	65.37	-0,61
Transportation cost from supplier to warehouse (€)	3428.7	3428.7	0.000%	3460.1	+0,92
Transportation cost from warehouse to hospitals (€)	9867.4	9867	-0.004%	9862.7	-0,05
Inter-warehouse transportation cost (€)	137.52	153.27	+11.40%	141.36	+2,79
Total cost (€)	13991	14008	+0.122%	14189	+1,42

* When the shelf-life parameter is set to new value (3,12) instead of two in the base case model solution, the inventory holding cost increases by 0.606% and +52,23%.

waste management. The integration of IFS-FUCOM and COPRAS within a hybrid structure systematically addresses uncertainty in managerial judgments while maintaining low computational complexity. Including shelf-life and inventory risk considerations in the optimization process offers a tangible advantage by minimizing waste costs and advancing sustainability objectives.

The framework supports strategic supply chain management by enabling organizations to balance LARG strategies. Incorporating risk and penalty parameters allows transparent identification of suppliers capable of maintaining operational stability during disruptions such as pandemics or supply crises. The proposed approach establishes a dynamic, data-driven system in which supplier performance scores are directly translated into order allocation decisions, supporting both forward and reverse logistics processes.

The Mixed-Integer Linear Programming (MILP) model developed in this study provides substantial operational flexibility and strategic foresight in inventory management and stock control. The model mitigates costly risks, including overstocking and stock shortages, by simultaneously optimizing critical parameters such as product shelf life, demand uncertainty, and holding costs. This is particularly relevant in sectors that manage perishable goods, such as food and pharmaceuticals, and in contexts that require temperature-controlled logistics. Proactive management of products before spoilage enhances operational efficiency, reducing financial losses and waste generation. This approach contributes to overall supply chain agility by enabling more resilient planning in the face of demand fluctuations. The model addresses the entire logistics network by optimizing product transfers between warehouses and resource utilization, thereby increasing efficiency in multi-location distribution systems. Implementing intelligent transfer planning strategies that redistribute surplus inventory from warehouses to points of need eliminates unnecessary supply expenditures and reduces transportation times and costs. This approach promotes efficient resource use in the scale distribution networks and enhances the ability to respond quickly to market demand, facilitating coordination among locations for managerial personnel.

From a sustainability and waste-management perspective, the model's closed-loop supply chain approach incorporates recycling processes into operational decision-making. Systematic planning for the revaluation of products nearing the end of their

shelf life or becoming obsolete reduces environmental impacts and establishes a cost-saving mechanism aligned with "Lean-Green" strategies. This integration aligns corporate social responsibility objectives with financial profitability.

Consequently, the MILP-based integrated model serves as a data-driven decision support mechanism across a wide range of functions, from supplier performance-based order planning to logistics cost optimization. Integrating waste management and recycling processes into daily operational decisions enables the establishment of strategic supply chain objectives on a scientific, traceable basis, rather than focusing solely on short-term concerns. This transparent, analytical structure allows decision-makers to manage corporate resources more effectively and achieve a sustainable competitive advantage in complex supply chain networks.

IV. CONCLUSION

Recent global supply chain disruptions have created operational uncertainty by significantly altering demand patterns, logistics processes, and consumer behavior. These changes underscore the urgent need to re-evaluate core supply chain components, particularly network design and supplier selection, to address both current and future challenges. Accordingly, this study highlights the strategic importance of establishing a sustainable supply chain structure in dynamic market conditions.

This study proposes an advanced optimization model for order allocation within a closed-loop supply chain (CLSC), specifically addressing product perishability and supplier performance under supply uncertainty. The model employs a comprehensive approach by tracking product flows among supply chain actors and warehouses, while closely monitoring inventory levels and potential waste. The framework incorporates a supplier selection methodology that integrates traditional and social criteria, as well as LARG principles. Pandemic-specific challenges are also addressed, enhancing the model's relevance in dynamic, uncertain environments. The multi-period model incorporates key factors such as inter-actor transportation costs, inventory holding costs, waste disposal costs, and penalties for low sustainability performance into the CLSC network design, thereby promoting sustainable supplier choices and environmentally responsible logistics practices. The problem is formulated as a probabilistic mixed-integer linear programming (MILP) model.

Supplier evaluation within the proposed mathematical model utilizes a score parameter, calculated through a novel integration of multiple multi-criteria decision-making (MCDM) methods. Evaluation criteria are identified through an extensive literature review, encompassing traditional, social, pandemic-specific, and LARG dimensions. These criteria are further refined with input from an expert panel comprising a procurement manager, a clinical trainer, and a supply chain researcher. The integrated application of Intuitionistic Fuzzy Sets (IFS), Fully Consistency Method (FUCOM), and Complex Proportional Assessment Method (COPRAS) facilitates the evaluation of decision makers, proposed criteria, and suppliers. This approach enables selecting the highest-priority options across varying capacity scenarios.

The originality of this study is demonstrated by the proposed model's capacity to restructure existing methods and offer innovative solutions to uncertainty and inefficiency in supply chain management. Within a closed-loop network design, the model systematically manages product movement between warehouses, monitors waste generation, and directs waste to recycling centers. Scenario-based analyses are conducted to evaluate pandemic-driven supply uncertainty, and supplier performance is assessed through the integration of IFS, FUCOM, and COPRAS methods. The development of flexible, sustainable decision-making mechanisms for dynamic, uncertain environments constitutes a significant contribution. This comprehensive approach advances both theoretical literature and practical applications, providing novel perspectives for addressing supply chain challenges.

The model was evaluated within a hospital network in Türkiye, focusing on tracking product flow across hospitals, depots, and recycling centers. Results show that supplier scores significantly affect product distribution, inventory levels, and waste costs across high-, medium-, and low-capacity scenarios. This study contributes to healthcare supply chain research, particularly in the management of perishable items under uncertain conditions.

Several research directions can further extend and deepen the scope of the proposed model. Integrating statistical methods and machine learning techniques into demand forecasting may improve accuracy and flexibility in managing uncertainty. Expanding the supplier network internationally will enable comprehensive risk and opportunity analysis across regions. Revising cost weighting methods and criteria sets in MCDM processes represents a significant opportunity to enhance optimization performance. Assessing the model's applicability across various sectors and enterprise sizes will yield insights into its generalizability and practical relevance. Incorporating sustainability performance indicators, such as carbon footprint and energy efficiency, will facilitate the development of new approaches for managing environmental impacts. Multidisciplinary studies are essential to further strengthen the theoretical and practical contributions of the proposed model.

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REFERENCES

- [1] T. M. Choi, "Fighting against COVID-19: what operations research can help and the sense-and-respond framework", *Annals of Operations Research*, early access, doi: 10.1007/S10479-021-03973-w.
- [2] F. Amimo, B. Lambert, A. Magit, M. Hashizume, "A review of prospective pathways and impacts of COVID-19 on the accessibility, safety, quality, and affordability of essential medicines and vaccines for universal health coverage in Africa", *Globalization and Health*, 17(1), (2021), 42.
- [3] A. Majumdar, M. Shaw, S. K. Sinha, "COVID-19 debunks the myth of socially sustainable supply chain: A case of the clothing industry in South Asian countries", *Sustainable Production and Consumption*, 24, (2020), 150–155.
- [4] F. Naz, A. Kumar, A. Majumdar, R. Agrawal, "Is artificial intelligence an enabler of supply chain resiliency post COVID-19? An exploratory state-of-the-art review for future research", *Operations Management Research*, 15(1-2), (2022), 378-398.
- [5] R. D. Tordecilla, A. A. Juan, J. R. Montoya-Torres, C. L. Quintero-Araujo, J. Panadero, "Simulation-optimization methods for designing and assessing resilient supply chain networks under uncertainty scenarios: A review", *Simulation Modeling Practice and Theory*, 106, (2021), 102166.
- [6] P. Suryawanshi, P. Dutta, "Optimization models for supply chains under risk, uncertainty, and resilience: A state-of-the-art review and future research directions", *Transportation Research Part E-Logistics and Transportation Review*, 157, (2022), 102553.
- [7] M. Rauf, M. Imran, J. Mumtaz, S. Javed, A. Saeed, "Multi-period supply chain optimization with contango and backwardation effects using an improved hybrid genetic algorithm", *Decision Science Letters*, 14(3), (2025), 587–602.
- [8] U. Illahi, M. S. Mir, "Maintaining efficient logistics and supply chain management operations during and after coronavirus (COVID-19) pandemic: learning from the past experiences", *Environment Development and Sustainability*, 23(8), (2021), 11157–11178.
- [9] R. Sharma, A. Shishodia, S. Kamble, A. Gunasekaran, A. Belhadi, "Agriculture supply chain risks and COVID-19: mitigation strategies and implications for the practitioners", *International Journal of Logistics Research and Applications*, 27(11), (2024), 2351-2377.
- [10] E. Taghizadeh, S. Venkatachalam, R. B. Chinnam, "A dynamic resilience management framework for deep-tier supply networks", *Cleaner Logistics and Supply Chain*, 13, (2024), 100174.
- [11] H. Carvalho, S. Azevedo, V. Cruz-Machado, "Trade-offs among Lean, Agile, Resilient and Green Paradigms in Supply Chain Management: A Case Study Approach", Editors: J. Xu, J. Fry, B. Lev, A. Hajiyev, *Proceedings of the Seventh International Conference on Management Science and Engineering Management*, 1st Edition, Springer Berlin, Heidelberg, 2014, 953–968, doi: 10.1007/978-3-642-40081-0_81.
- [12] J. M. Bloemhof, M. Soysal, "Sustainable Food Supply Chain Design", Editors: Y. Bouchery, C. Corbett, J. Fransoo, T. Tan, *Sustainable Supply Chains*, 1st Edition, Springer Cham, 2017, pp. 395–412, doi: 10.1007/978-3-319-29791-0_18.
- [13] S. G. Azevedo, H. Carvalho, V. Cruz-Machado, "LARG index A benchmarking tool for improving the leanness, agility, resilience and greenness of the automotive supply chain", *Benchmarking-An International Journal*, 23(6), (2016), 1472–1499.
- [14] R. D. Raut, S. K. Mangla, V. S. Narwane, M. Dora, M. Q. Liu, "Big Data Analytics as a mediator in Lean, Agile, Resilient, and Green (LARG) practices effects on sustainable supply chains", *Transportation Research Part E-Logistics and Transportation Review*, 145, (2021), 102170.
- [15] F. Lanzalonga, S. Likavec, P. P. Biancone, "Balancing profit and sustainability: Assessing the impact of European Union environmental policies on the automotive sector" *Research in Transportation Business and Management*, 60, (2025), 101359.

- [16] V. D. R. Guide, L. N. Van Wassenhove, "The evolution of closed-loop supply chain research", *Operations Research*, 57(1), (2009), 10–18.
- [17] K. S. Moghaddam, "Supplier selection and order allocation in closed-loop supply chain systems using hybrid Monte Carlo simulation and goal programming", *International Journal of Production Research*, 53(20), (2015), 6320–6338.
- [18] M. Mohammadzadeh, A. A. Khamseh, M. Mohammadi, "A multi-objective integrated model for closed-loop supply chain configuration and supplier selection considering uncertain demand and different performance levels", *Journal of Industrial and Management Optimization*, 13(2), (2017), 1041–1064.
- [19] S. Ahmadi, S. H. Amin, "An integrated chance-constrained stochastic model for a mobile phone closed-loop supply chain network with supplier selection", *Journal of Cleaner Production*, 226, (2019), 988–1003.
- [20] K. Govindan, J. D. Darbari, V. Agarwal, P. C. Jha, "Fuzzy multi-objective approach for optimal selection of suppliers and transportation decisions in an eco-efficient closed loop supply chain network", *Journal of Cleaner Production*, 165, (2017), 1598–1619.
- [21] S. H. Amin, G. Zhang, "An integrated model for closed-loop supply chain configuration and supplier selection: Multi-objective approach", *Expert Systems with Applications*, 39(8), (2012), 6782–6791.
- [22] G. Cavone, M. Dotoli, N. Epicoco, D. Morelli, C. Seatzu, "Design of Modern Supply Chain Networks Using Fuzzy Bargaining Game and Data Envelopment Analysis", *IEEE Transactions on Automation Science and Engineering*, 17(3), (2020), 1221–1236.
- [23] S. J. Ghouschi, I. Hushyar, "Designing a closed-loop supply chain network and providing a multi-objective mathematical model to select a third-party logistics company and supplier simultaneously", *International Journal of Industrial Engineering-Theory Applications and Practice*, 27(2), (2020), 245–275.
- [24] A. K. Nasr, M. Tavana, B. Alavi, H. Mina, "A novel fuzzy multi-objective circular supplier selection and order allocation model for sustainable closed-loop supply chains", *Journal of Cleaner Production*, 287, (2021), 124994.
- [25] S. Rouhani, S. H. Amin, L. Wardley, "A novel multi-objective robust possibilistic flexible programming to design a sustainable apparel closed-loop supply chain network", *Journal of Environmental Management*, 365, (2024), 121496.
- [26] N. Varshney, S. Gupta, A. Ahmed, "Addressing uncertainty in closed-loop supply chain networks: a multi-objective approach to integrated production and transportation problems Closed-loop supply chain networks", *Journal of Modelling in Management*, 19(6), (2024), 1849–1882.
- [27] S. B. Ebrahimi, "A stochastic multi-objective location-allocation-routing problem for tire supply chain considering sustainability aspects and quantity discounts", *Journal of Cleaner Production*, 198, (2018), 704–720.
- [28] S. M. Kisomi, M. Solimanpur, A. Doniavi, "An integrated supply chain configuration model and procurement management under uncertainty: A set-based robust optimization methodology", *Applied Mathematical Modeling*, 40(17–18), (2016), 7928–7947.
- [29] S. Rezaei, I. Ghalekhondabi, M. Rafiee, S. N. Zanganeh, "Supplier selection and order allocation in CLSC configuration with various supply strategies under disruption risk", *Opsearch*, 57(3), (2020), 908–934.
- [30] A. J. Ruiz-Torres, F. Mahmoodi, S. Ohmori, A. Hlali, "Suppliers portfolio and returner incentive decisions in closed-loop remanufacturing systems under multiple stochastic scenarios", *International Journal of Sustainable Engineering*, 15(1), (2022), 210–227.
- [31] M. Momenitabar, Z. D. Ebrahimi, M. Arani, J. Mattson, "Robust possibilistic programming to design a closed-loop blood supply chain network considering service-level maximization and lateral resupply", *Annals of Operations Research*, 328(1), (2023), 859–901.
- [32] G. Ghiani, G. Laporte, R. Musmanno, *Introduction to Logistics Systems Management*, Second Edition, John Wiley & Sons, 2013.
- [33] S. Chopra, P. Meindl, *Supply chain management: strategy, planning, and operation*, Sixth Edition, Pearson, 2016.
- [34] M. Soysal, J. M. Bloemhof-Ruwaard, R. Haijema, J. G. A. J. Van Der Vorst, "Modeling an Inventory Routing Problem for perishable products with environmental considerations and demand uncertainty", *International Journal of Production Economics*, 164, (2015), 118–133.
- [35] S. Erişkan, "Tedarikçi seçimi ve entegre kapalı döngü tedarik zinciri ağ tasarımı problemleri için bir karar destek sistemi", *Doktora Tezi*, Burdur Mehmet Akif Ersoy Üniversitesi Sosyal Bilimler Enstitüsü, Burdur, Türkiye, 2023.
- [36] A. Çınar, Ö. Uygun, "Sezgisel Bulanık AHP Yöntemiyle Yeşil Tedarikçi Seçimi", *Zeki Sistemler Teori ve Uygulamaları Dergisi*, 2(2), (2019), 24–31.
- [37] K. T. Atanassov, "Intuitionistic fuzzy sets", *Fuzzy Sets and Systems*, 20(1), (1986), 87–96.
- [38] Z. B. Kanik, S. Erişkan, M. Soysal, M. Ömürganülşen, "A hybrid approach based on qualitative and quantitative techniques for analyzing last-mile parcel delivery", *Opsearch*, early access, doi: 10.1007/S12597-025-01017-6.
- [39] H. W. Liu, G. J. Wang, "Multi-criteria decision-making methods based on intuitionistic fuzzy sets", *European Journal of Operational Research*, 179(1), (2007), 220–233.
- [40] M. S. Yurtyapan, "Kurumsal kaynak planlaması yazılım tercihinde Macbeth karar verme metodunun aralık gri sayı yaklaşımı ile geliştirilmesi", *Yüksek Lisans Tezi*, Süleyman Demirel Üniversitesi Fen Bilimleri Enstitüsü, Isparta, Türkiye. 2019.
- [41] B. D. Rouyendegh, A. Yildizbasi, P. Üstünyer, "Intuitionistic Fuzzy TOPSIS Method for Green Supplier Selection Problem", *Soft Computing*, 24(3), (2020), 2215–2228.
- [42] M. S. Yurtyapan, E. Aydemir, "ERP software selection using intuitionistic fuzzy and interval grey number-based MACBETH method", *Grey Systems Theory & Application*, 12(1), (2022), 78–100.
- [43] H. Z. Kine, Z. Shiferaw, G. Gebresenbet, L. Tavasszy, D. Ljungberg, "GIS based multi-criteria decision-making approach for dry port location analysis: The case of Ethiopia", *Research in Transportation Business and Management*, 60, (2025), 101370.
- [44] D. Pamucar, I. Badi, K. Sanja, R. Obradovic, "A Novel Approach for the Selection of Power-Generation Technology Using a Linguistic Neutrosophic CODAS Method: A Case Study in Libya", *Energies*, 11(9), (2018), 2489.
- [45] Y. Şahin, K. Karagül, "FUCOM ve COPRAS Yöntemleriyle ERP Yazılımı Seçimi", *International Conference on Applied Engineering and Natural Sciences*, Konya, Türkiye, 10–13 November 2022.
- [46] F. Ecer, "FUCOM subjektif ağırlıklandırma yöntemi ile rüzgâr çiftliği yer seçimini etkileyen faktörlerin analizi", *Pamukkale Üniversitesi Mühendislik Bilimleri Dergisi*, 27(1), (2021), 24–34.
- [47] D. Pamucar, Z. Stevic, S. Sremac, "A new model for determining weight coefficients of criteria in mcdm models: Full consistency method (fucom)", *Symmetry-Basel*, 10(9), (2018), 393.
- [48] G. Fancello, M. Carta, P. Serra, "Data Envelopment Analysis for the assessment of road safety in urban road networks: A comparative study using CCR and BCC models", *Case Studies on Transport Policy*, 8(3), (2020), 736–744.
- [49] E. Kazimieras Zavadskas, A. Kaklauskas, V. Šarka, "The new method of multicriteria complex proportional assessment of projects", *Technological and Economic Development of Economy*, 1(3), (1994), 131–139, <https://www.researchgate.net/publication/285902199>.
- [50] S. Hezer, E. Gelmez, E. Özceylan, "Comparative analysis of TOPSIS, VIKOR and COPRAS methods for the COVID-19 Regional Safety Assessment", *Journal of Infection and Public Health*, 14(6), (2021), 775–786.
- [51] B. Matic, S. Jovanovic, D. K. Das, E. K. Zavadskas, Z. Stevic, S. Sremac, M. Marinkovic, "A new hybrid MCDM model: sustainable supplier selection in a construction company", *Symmetry-Basel*, 11(3), (2019), 353.
- [52] S. Seker, F. B. Baglan, N. Aydin, M. Devci, W. P. Ding, "Risk assessment approach for analyzing risk factors to overcome pandemic using interval-valued q-rung orthopair fuzzy decision-making method", *Applied Soft Computing*, 132, (2023), 109891.
- [53] Y. H. Zheng, Z. S. Xu, Y. He, H. C. Liao, "Severity assessment of chronic obstructive pulmonary disease based on hesitant fuzzy linguistic COPRAS method", *Applied Soft Computing*, 69, (2018), 60–71.
- [54] M. Soysal, "Closed-loop Inventory Routing Problem for returnable transport items", *Transportation Research Part D-Transport and Environment*, 48, (2016), 31–45.
- [55] A. Afrasiabi, M. Tavana, D. Di Caprio, "An extended hybrid fuzzy multi-criteria decision model for sustainable and resilient supplier selection", *Environmental Science and Pollution Research*, 29(25), (2022), 37291–37314.
- [56] A. Fallahpour, M. Yazdani, A. Mohammed, K. Y. Wong, "Green sourcing in the era of industry 4.0: towards green and digitalized competitive advantages", *Industrial Management & Data Systems*, 121(9), (2021), 1997–2025.
- [57] N. Goker, "A novel integrated intuitionistic fuzzy decision aid for agile outsourcing provider selection: a COVID-19 pandemic-based scenario analysis", *Soft Computing*, 25(21), (2021), 13723–13740.
- [58] M. Ilyas, S. Carpitella, E. Zoubir, "Designing supplier selection strategies under COVID-19 constraints for industrial environments", *Procedia CIRP*, 100, (2021), 589–594.

- [59] G. M. Magableh, M. Z. Mistarihi, "Applications of MCDM approach (ANP-TOPSIS) to evaluate supply chain solutions in the context of COVID-19", *Heliyon*, 8(3), (2022), e09062.
- [60] S. Pratap, Y. Daultani, A. Dwivedi, F. L. Zhou, "Supplier selection and evaluation in e-commerce enterprises: a data envelopment analysis approach", *Benchmarking-An International Journal*, 29(1), (2022), 325–341.
- [61] Z. L. Shang, X. Y. Yang, D. Barnes, C. Wu, "Supplier selection in sustainable supply chains: Using the integrated BWM, fuzzy Shannon entropy, and fuzzy MULTIMOORA methods", *Expert Systems with Applications*, 195, (2022), 116567.
- [62] C. M. C. M. U-Dominic, I. J. Orji, M. Okwu, V. M. Mbachu, "The Impact of Covid-19 Pandemic on Sustainable Supplier Selection Process", *Advancing Industrial Engineering in Nigeria through Teaching, Research and Innovation*, Department of Industrial and Production Engineering, University of Ibadan, 2020, <https://www.researchgate.net/publication/350637845>.
- [63] A. Mohammed, M. Yazdani, A. Oukil E. D. R. S. Gonzalez, "A Hybrid MCDM Approach towards Resilient Sourcing", *Sustainability*, 13(5), (2021), 2695.
- [64] Z. Wang, F. Y. Xiao, Z. H. Cao, "Uncertainty measurements for Pythagorean fuzzy set and their applications in multiple-criteria decision making", *Soft Computing*, 26(19), (2022), 9937–9952.
- [65] I. J. Orji, F. Ojadi, "Investigating the COVID-19 pandemic's impact on sustainable supplier selection in the Nigerian manufacturing sector", *Computers and Industrial Engineering*, 160, (2021), 107588.
- [66] Y. F. Shao, D. Barnes C. Wu, "Sustainable supplier selection and order allocation for multinational enterprises considering supply disruption in COVID-19 era", *Australian Journal of Management*, 48(2), (2023), 284–322.
- [67] S. H. H. Petrudi, H. B. Ahmadi, A. Rehman, J. J. H. Liou, "Assessing suppliers considering social sustainability innovation factors during COVID-19 disaster", *Sustainable Production and Consumption*, 27, (2021), 1869–1881.
- [68] T. Chen, Y. C. Wang, "A calibrated piecewise-linear FGM approach for travel destination recommendation during the COVID-19 pandemic", *Applied Soft Computing*, 109, (2021), 107535.
- [69] M. Tavana, A. R. Abtahi, D. Di Caprio, R. Hashemi, R. Yousefi-Zenouz, "An integrated location-inventory-routing humanitarian supply chain network with pre- and post-disaster management considerations", *Socio-Economic Planning Science*, 64, (2018), 21–37.
- [70] L. Poursoltan, S. M. Seyed-Hosseini, A. Jabbarzadeh, "Green Closed-Loop Supply Chain Network under the COVID-19 Pandemic", *Sustainability*, 13(16), (2021), 9407.
- [71] A. Mahmoudi, S. A. Javed, A. Mardani, "Gresilient supplier selection through Fuzzy Ordinal Priority Approach: decision-making in post-COVID era", *Operations Management Research*, 15(1–2), (2022), 208–232.

APPENDIX-A

Table A. A definitional framework of main and sub-criteria used in the decision-making process.

Main Group	Code	Criteria	Explanation	Reference
Traditional criteria C_1	C_{11}	Cost	The overall transportation cost incurred for delivering products to an Alternative location is ultimately transferred to the buyers.	[55],[56],[57],[58],[59],[60],[61],[62]
	C_{12}	Quality	Product features and service levels that meet customer needs in products, services and key components (e.g. certification, quality management, scrap quality).	[59],[63],[64]
	C_{13}	Risk Monitoring	Strategic oversight minimizes crisis impacts by assessing risks to assets, operations, and infrastructure, while ensuring supplier stability and continuity for effective emergency response.	[59],[61],[63]
	C_{14}	Geographic location	Distance between vendor and supplier locations.	[63]
Social criteria C_2	C_{21}	Employee competence	Efficient personnel assignment, robust health and safety measures, comprehensive training programs, and strict policy compliance.	[55],[59],[61],[62],[65],[66]
	C_{22}	Social responsibility	Transparent public disclosure, proactive response to stakeholder pressures, and clear communication to meet customer expectations, satisfaction, and engagement.	[56],[57],[65],[67],[61],[62],[66]
	C_{23}	Supplier reputation	Supplier reputation among company stakeholders.	[58],[61],[67],[68]
LARG-focused criteria C_3	C_{31}	Technical competence	Supplier adaptability to advanced manufacturing and technology ensures resilience to tech shocks.	[55],[59],[63]
	C_{32}	Use of advanced analytics	Ability to better understand issues, resolve unsolved challenges, and improve decision-making through advanced data analysis.	[55],[56],[57],[61],[66],[62],[64],[69]
	C_{33}	Ongoing collaborations	Equipped with both physical and digital capabilities to enhance collaboration among all supply chain actors.	[59],[61],[63]
	C_{34}	Agility and flexibility	Excess inventory, spare parts availability, and repair capacity.	[55],[59],[63],[70],[61],[66],[69]
	C_{35}	Vulnerability management	Strategic crisis planning is enhanced by agile threat response, achieved through a flexible and structured sales and operations planning framework	[55],[59]
	C_{36}	Visibility and responsiveness	Vendor willingness to share pertinent information with customers fosters transparency, builds trust, and facilitates better decision-making.	[57],[63],[69]
	C_{37}	Environmental management	Monitoring, evaluating, and controlling the supplier's environmental activities and policies, including certifications, continuous oversight, and regulatory compliance.	[55],[61],[62],[64],[65],[66],[71]
	C_{38}	Green competencies	The supplier employs strategies to minimize environmental impact throughout product life cycles, invests in sustainable product development (Including reuse design) and adapts processes to conserve natural resources.	[55],[56],[65],[71],[61],[62],[64],[66]
Pandemic-specific criteria C_4	C_{41}	Regulatory harmonization	Actively monitoring regulatory changes and swiftly adapting to maintain compliance.	[62],[65],[67]
	C_{42}	Social and cultural cohesion	Combining robust risk management with a thorough assessment of the company's social conditions during illness monitoring processes.	[62],[65],[67]
	C_{43}	Health threat	Personal protective equipment usage, pandemic severity, vaccination rates, safety practices, control performance, COVID-19 resilience, and government measures.	[59],[62],[65],[68]
	C_{44}	Diversified suppliers	The supplier portfolio's breadth ensures incoming orders are met.	[63],[67]