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Multi-Product, Multi-Period Sustainable Perishable Supply Chain Optimization with Uncertainty Navigation

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Abstract

This study creates a resilient and sustainable supply chain framework for perishable goods that harmonizes economic, environmental, and social goals. By tackling the intricacies associated with multi-tiered, multi-product, and multi-temporal systems, the study enhances supply chain efficiency in the face of uncertainty. The primary goal is to reduce costs, minimize environmental impacts, and improve service levels, while incorporating the unique characteristics of the dairy and pharmaceutical industries. The study utilizes a multi-objective mixed-integer linear programming framework to enhance the sustainability of a supply chain dedicated to perishable goods in the face of uncertainty. The model is validated using experimental data, solved with GAMS software and CPLEX solver, and further analyzed through the NSGA-II meta-heuristic algorithm and a modified epsilon constraint method. Comparative evaluations assess the performance and efficiency of these optimization techniques, highlighting their applicability in diverse supply chain scenarios. The study demonstrates that the NSGA-II algorithm outperforms the modified epsilon constraint algorithm in handling large-scale supply chain optimization problems, offering faster computation and more diverse Pareto-optimal solutions. Conversely, the epsilon constraint method provides greater precision and accuracy for smaller, less complex problems. The proposed models effectively balance economic, environmental, and social objectives, showcasing their applicability in designing sustainable and robust supply chains for perishable products under uncertainty.

Keywords: *Perishable Products, Sustainable Supply Chain, Uncertainty and Risk, Multi-Objective Optimization*

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1 INTRODUCTION: In an increasingly interconnected global economy, supply chains are pivotal for sustaining commerce and fulfilling consumer demand (Sahebi et al., 2024). Supply chains are not just logistical frameworks; they serve as the backbone of industries that deliver critical goods, including perishable items like food, dairy, medications, and blood-related products. As these products are highly sensitive to time and environmental conditions, their supply chain management requires precise planning and execution. With a growing population and heightened consumer expectations, ensuring the availability and quality of such products has become a formidable challenge (Shen et al., 2013). This complexity is further compounded by the significant environmental and social impacts inherent in the production, transportation, and disposal of perishable goods (Rafie-Majd et al., 2018). Addressing these challenges necessitates the development of innovative, sustainability-driven supply chain models that integrate economic, environmental, and social dimensions to enhance resilience and competitiveness. Supply chains compete with one another in commercial settings (Daghigh et al., 2016; Moghadam et al., 2022), as supply chains support the world economy and all organizations belong to at least one of them (Scholten & Fynes, 2017). The market is the most significant element in today’s competition, and supply chains in leading nations are built to enhance business conditions, lower costs, raise service levels (satisfaction), and boost competitiveness (Tavakkoli Moghaddam et al., 2019). Additionally, managing it is one of the biggest issues facing managers (Scholten & Fynes, 2017), which is why a number of risks and disruptions have over time made the supply chain more vulnerable, it brings up a crisis. Considering the necessity of this issue, supply chain managers should identify potential disturbances so that they can improve them (Firouzabad et al., 2024). The most basic decision in managing the design of the supply chain network is to integrate it so that the flow of materials is one of the most important factors to achieve efficiency and also, the supply chain is stable.

Thus, integration and integration of tactical, strategic, and operational decisions are required in order to fulfill this objective. By taking into account sustainability’s numerous aspects, such as its social, environmental, and economic objectives, a sustainable supply chain can be established (Taticchi et al., 2013). Research on the sustainability of perishable products necessitates a comprehensive approach, and the three aspects of sustainability—particularly the social dimension, which is underemphasized in studies—should be taken into account (Feil et al., 2020). Sustainable development addresses present needs while ensuring that future generations can fulfill their own requirements without compromising their ability to do so (Asgharizadeh et al., 2019). Due to population growth and the rising demand for dairy products, this significance is now increasingly important (Jouzdani et al., 2013). Also, the production and consumption of dairy products have considerable effects on the environment and are one of the most polluted industries (Feil et al., 2020). The healthcare sector is experiencing a global rise in costs, with pharmaceuticals representing a significant portion of these expenses. Despite the progress made in commercial supply chain manufacturing, storage, and distribution, numerous pharmaceutical companies continue to fall short of meeting the demands of the market. As a result, the pharmaceutical supply chain needs to employ effective optimization approaches (Savadkoohi et al., 2018).

Perishability and the lifespan of perishable products strongly influence the three sustainability criteria (Scholten & Fynes, 2017). The transient characteristics of food and pharmaceuticals, which possess a finite shelf life, are of significant concern owing to the substantial waste generated, detrimental environmental impacts, and the specific requirements for their storage and transportation. These products are also impacted by rising inflation rates, rising transportation expenses, rising petrochemical prices (which are important for packaging these kinds of goods), and rising cost fluctuations production, high rate of perishability and cost of storage. Assuming that items are perishable, the limited shelf life of these goods can be attributed to supply chain network design, which includes issues with raw materials, inventory volume, transportation techniques, routes, and product flow (Asgharizadeh et al., 2019). Medicine and dairy products are considered perishable items and should be sold before they spoil or near their expiration date to maximize profit. This rule does not apply to these products. The importance of this issue allows for the assertion that the primary objective of supply chain risk management is to mitigate the effects of these risks through the development of models and methodologies designed for the identification, evaluation, and reduction of supply chain vulnerabilities (Jouzdani et al., 2013). Risk is not given much thought by domestic organizations; even developed nations have arrived at this conclusion. The entire organization must be involved in the active and methodical management of risk, taking supply chain unpredictability into account (Shen et al., 2013). It serves as a safety net in terms of time, capacity, inventory, and other factors to stop the chain from performing poorly (Rafie-Majd et al., 2018). Despite significant advancements in supply chain optimization, the management of perishable goods remains fraught with risks and inefficiencies. The limited shelf life of dairy and pharmaceutical products exacerbates issues related to waste, storage costs, and environmental degradation, while fluctuations in transportation and production costs create additional layers of uncertainty. Incorporating sustainability into supply chain design presents a viable path to overcoming these challenges. The integration of tactical, strategic, and operational decision-making processes is essential for establishing a sustainable and resilient supply chain that effectively reconciles economic performance with social equity and environmental responsibility (Meidute-Kavaliauskiene et al., 2021).

Recent advancements in sustainable perishable supply chain models have integrated emerging technologies and multi-dimensional sustainability considerations. For instance, Kumar and Agrawal (2024) introduced a quality-based architecture employing image processing model to classify perishable produce—specifically tomatoes—at different supply chain stages, thereby enabling more informed procurement and pricing decisions. Their model, integrating industry 4.0 principles, achieved an 88.4% accuracy rate and significantly improved decision-making speed, reducing losses due to perishability. This reflects an evolving paradigm where AI-based inspection systems optimize freshness-based logistics, contributing simultaneously to economic, environmental, and social goals. Additionally, recent studies have incorporated renewable energy systems and uncertainty modeling to improve energy resilience and minimize emissions in cold chain logistics (Huang et al., 2024), and proposed decision frameworks for sustainable supplier selection and order allocation in food supply chains under fuzzy environments (Kumar et al., 2025). These contributions collectively emphasize that the effective integration of perishability, environmental constraints, and supply network resilience is key to achieving sustainable performance in modern supply chains. This study enhances the existing literature by formulating a multi-objective, mixed-integer linear programming model aimed at optimizing supply chains that are characterized by multiple levels, products, and time periods, all while accounting for uncertainty. It provides a novel perspective on managing disruptions and addressing the unique challenges of perishability, ensuring both profitability and sustainability in supply chain operations.

2 THEORETICAL BACKGROUND: Perishable products cannot be saved for a long time. Therefore, as long as these goods are transferred from one level of the chain to another, they are subject to expiration or damage, and their damage depends on the type of goods. Every supply chain aims to satisfy demands and with the maximum efficiency and lowest cost. For instance, certain commodities perish faster when the temperature surrounding them increases, so the storage conditions of perishable products also affect them. Retailers, wholesalers, distributors, manufacturers, and suppliers are all part of the supply chain, and each one of them satisfies the needs of the end consumers (Meidute-Kavaliauskiene et al., 2022). Numerous investigators have conducted studies in this domain, which are presented in the Table 1.

Table 1. The review of related literature.

No.	**Author**	Supply Chain Levels			Product Lifecycle		Sustainability Dimensions			Network Design					Solution Method
		Retailer	Manufactur er	Supplier	Fix	Stochastic	Economic	Social	Environmen tal	Inventory	Allocation	Routing	Location	Scheduling	
1	(Kumar et al., 2025)		*	*		*	*	*	*		*	*			Fuzzy MILP, Goal Pro
2	(Kumar &		*		*		*		*	*				*	CNN, DOE

	Agrawal, 2024)														
3	(Huang et al., 2024)		*	*	*		*		*		*	*			PSO
4	(Komijani & Sajadieh, 2024)	*	*		*		*	*				*	*		PSO, SA
5	(Souri & Fatemi Ghomi, 2024)		*		*		*		*		*			*	MILP
6	(Heidari & Rabbani, 2023)	*	*		*		*	*	*						NSGA II
7	(Tirkolaee & Aydin, 2022)	*	*	*	*		*	*	*	*			*		GA
8	(Yadav et al., 2022)	*	*	*			*	*	*						Bender's decomposing
9	(Yazdani et al., 2022)	*	*	*	*		*	*							Fuzzy stochastic programming
10	(Shafiee et al., 2021)	*	*	*	*		*	*	*	*					LP metric
11	(Mohebalizadehgashti et al., 2020)	*	*	*	*		*		*						Epsilon constraint
12	(Sazvar & Sepehri, 2020)			*		*	*	*	*	*					Epsilon constraint
13	(Rabbani et al., 2019)	*	*	*	*		*		*		*	*	*		Robust programming
14	(Onggo et al., 2019)	*		*	*			*	*						Monte Carlo simulation
15	(Diabat et al., 2019)	*		*	*				*		*	*			Lagrangian relaxation
	(Yavari & Zaker, 2019)	*	*		*		*		*	*			*		LP metric
16	(Bottani et al., 2019)			*	*										ACO
17	(Darestani & Hemmati, 2019)	*	*	*	*		*		*						Multicriteria optimization
18	(Deng et al., 2019)	*	*	*		*									Stochastic programming
19	(Jonkman et al., 2019)		*	*	*										Epsilon constraint

20	(Hsu, 2019)	*	*	*		*	*	*	*				*		Compromise Programming
21	(Eskandari-Khanghahi et al., 2018)	*	*	*	*		*	*	*		*				SA
22	(Aggarwal, 2018)		*	*	*		*		*	*					Goal programming
23	(Navazi et al., 2019)		*	*	*			*				*			Epsilon constraint
24	(Fan & Fan, 2018)			*		*		*							Epsilon constraint
25	(Dai et al., 2018)	*		*	*			*			*				Epsilon constraint
26	(Savadkoohi et al., 2018)	*	*		*			*			*				NSGA II
27	(Grillo et al., 2017)			*		*									NSGA II, MOPSO
28	(Musavi & Bozorgi-Amiri, 2017)			*	*		*		*				*	*	Epsilon constraint
29	(de Keizer et al., 2017)			*		*							*		Robust optimization
30	(Zahiri & Pishvaee, 2017)	*	*	*	*		*				*		*		LP metric
31	This Research	*	*	*	*		*	*	*		*	*	*		NSGA II, Robust optimization

A detailed review of reveals that several scholars (e.g., Sazvar & Sepehri, 2020; Yadav et al., 2022) took social, environmental, and economic factors into account while modeling the perishable products supply chain (Heidari & Rabbani, 2023; Tirkolaee & Aydin, 2022). The carbon emission index was considered as a widely used and valid index for determining environmental effects. Some scholars (Govindan et al., 2015; Shafiee et al., 2021; Tirkolaee & Aydin, 2022) considered some parameters as uncertain, some (Yavari & Geraeli, 2019; Zahiri & Pishvaee, 2017) saw stable optimization, and some (de Keizer et al., 2017; Ma et al., 2019; Shrivastava et al., 2018) considered uncertainty as random in the supply chain of perishable items. Two issues that are being addressed in this field of research are the limiting of the problem in the case chain and the issue of expiration in the objective function (Al Shamsi et al., 2014; Chen & Zhong, 2013; Grillo et al., 2017). In the research field, Rabbani et al. (2020) created multi-cycle supply chains with several products, and Raut et al. (2020) took the fixed life index into account while designing perishable item supply chains. This study proposes a novel combination and model for the supply chain of multi-product and multi-cycle perishable items. This new approach takes into account the fixed life of the product and operates in a certainty-based environment for perishable products. This differs from the previous research, which explored various other cases in this domain. Recent research reflects a growing emphasis on hybrid AI models, renewable energy resilience, and scenario-based optimization for perishable goods. Kumar and Agrawal (2024) apply deep learning and DOE to enhance grading accuracy of tomatoes, while Huang et al. (2024) address cold chain resilience through renewable energy planning. Similarly, other works (Komijani & Sajadieh, 2024; Kumar et al., 2025; Souri & Fatemi Ghomi, 2025) demonstrate the importance of integrating perishability, sustainability, and operational uncertainty into mathematical supply chain models. These recent studies underscore the dynamic evolution of this field and highlight critical paths for future exploration.

The supply chain network must be designed with the utmost care since there are long-term consequences of network design on supply chain performance, and short-term adjustments to the network design are expensive and time-consuming (Sadeghi Moghadam et al., 2024). Comparing this model to earlier studies, it differs in the following ways: multi-level, multi-product, multi-period with four-level product inventory levels for perishable products and uncertainty in demand, price, damage-related costs, and extent of damage. Since perishable items are effective in public health, and their distribution is associated with risk, the perishability of pharmaceutical and dairy products as a case study with fixed life index, and the cost of product failure, is being considered in the proposed model. The suggested model also takes into account allocation, the balancing of related expenses (cost function), the calculation of production and distribution pricing decisions, and the emission costs of NOX, HC, CO2, and CO (environmental cost function). Taking into account the environmental tax, the possibility of a disruption in the perishable sustainable supply chain network's architecture, and seven social indicators, the primary features of this study include training, job satisfaction, accidents, lost working days, health and safety, non-discriminatory hiring and firing, and validation of the suggested model and solution approaches using actual case studies in two separate Tehran/Iran organizations.

3 RESEARCH METHODOLOGY: To effectively model and advance the supply chain for perishable goods, this study examines critical issues that have been largely overlooked in existing research literature, employing an evolutionary perspective. These issues are presented as one main issue and three smaller issues. The primary concern of creating a four-tiered, multi-stage supply chain network that is sustainable is incorporating distributors, producers, suppliers, and the target market, or retailers. In this chain, it is assumed that the manufacturer collects and produces the required raw materials from several suppliers to produce several perishable products, and the suppliers send the required raw materials to the production factory immediately after the order. It is also a production center (pharmaceutical and dairy); it produces perishable goods and sends them to distribution centers and retailers to meet the request of the final customer. The manufactured products have a fixed life (expiry date), and if the products sent to the retailers are damaged or expired, they will be returned to the distributor channel and from there to the manufacturer. The manufacturer's inventory is insufficient as a result of the suppliers' failure to provide the raw materials. In the first sub-problem, product freshness has been taken into consideration in the objective and limitation function in order to compute economic value, include perishability in production modeling, and use product life as a loss or profit function. Minimizing the cost of perishability of products due to disruptions in the network and reducing demand, the cost of returning products due to the reduction of quality level (freshness) and the cost of product damage due to transportation, production and packaging. The second sub-problem is that the current models are ineffective under these circumstances, since the disruption of the facilities alters the model's structure or the network. In actuality, there are several kinds of disruptions on transit routes. As a result, the design of these models ought to be such that disruption risks do not interfere with their effectiveness. In this section, we are attempting to look into the possibility of facilities and suppliers experiencing disruptions in the chain network design.

This case is being addressed under the third issue because the aspects of costs, appropriate resource use, and balanced attention to the field of sustainability in the supply chain are significant. In the first stage, to choose the appropriate social indicators with attention to the background related to the social dimension of sustainability, gathering social indicators and identifying the most important ones by identifying experts in the company (pharmaceutical and dairy products) were investigated and 19 social indicators were identified and were screened using the fuzzy delphi method (FDM). According to research specialists, departure, health and safety, employment without discrimination, and dismissal were all placed, validated, and employed in mathematical modeling to carry out the procedure. The fuzzy delphi method's results displayed in Table 2.

Table 2. Result of FDM for social criteria

Index No.	Indicator	Fuzzy value			Crisp value	Decision
		L	M	U		
SC1	Non-discriminatory Hiring	0.25	0.5626	1	0.6042	Approved
SC2	Promotion Based on Merit	0	0.4452	1	0.4817	Rejected
SC3	Health and Safety	0.25	0.6878	1	0.6459	Approved
SC4	Use of Standard and Non-hazardous Materials	0	0.3618	1	0.4539	Rejected
SC5	Prohibition of Child Labor	0	0.4227	1	0.4742	Rejected
SC6	Job Creation	0.25	0.1247	1	0.4582	Rejected
SC7	Humanitarian Activities	0	0.4922	1	0.4974	Rejected
SC8	Training	0.25	0.5121	1	0.5874	Approved
SC9	Dismissal	0.25	0.3658	1	0.5386	Approved
SC10	Fair Wage Payment and Compensation	0	0.4548	1	0.4849	Rejected
SC11	Lost Workdays	0	0.6852	1	0.5617	Approved
SC12	Working Hours	0	0.4011	1	0.467	Rejected
SC13	Accidents	0.25	0.6322	1	0.6274	Approved
SC14	Job Satisfaction	0	0.6338	1	0.5446	Approved
SC15	Employee Engagement	0	0.4731	1	0.491	Rejected
SC16	Traffic Congestion	0	0.5597	1	0.5199	Rejected
SC17	Regional Economic Development	0	0.4765	1	0.4922	Rejected
SC18	Cultural Preservation	0	0.5402	1	0.5134	Rejected
SC19	Job Stability	0	0.5274	1	0.5091	Rejected

Expert evaluations from both pharmaceutical and dairy sectors were converted into fuzzy numbers, and defuzzified using the centroid method to produce crisp values. The threshold for acceptance was determined by calculating the average crisp score across all indicators (Delshad et al., 2018). Indicators with a crisp value greater than or equal to this average (≈ 0.523) were considered "approved." SC14 with a crisp value of 0.5446 exceeded the threshold and was approved, while SC16 with a value of 0.5199 did not meet the cutoff and was rejected.

The proposed multi-objective mixed-integer nonlinear programming (MINLP) model was implemented using the general algebraic modeling system (GAMS 24.8.5) and solved using the CPLEX solver, which is widely used for large-scale linear and mixed-integer optimization problems. Additionally, the NSGA-II algorithm was implemented in MATLAB R2021a for meta-heuristic analysis and Pareto front generation.

The development of the model requires several foundational assumptions that reflect realistic supply chain behaviors under uncertainty. The following subsection outlines these assumptions, which form the basis for the mathematical formulation.

***3.1. Model assumptions*:** The mathematical model proposed in this study is formulated as a MINLP framework that simultaneously optimizes economic, environmental, and social performance indicators of a perishable product supply chain. It accounts for various uncertainty dimensions including demand volatility, expiration rates, and environmental taxes. The mathematical model assumption are as follows:

- Various types of perishable products have been considered for designing the supply chain network (Darestani & Hemmati, 2019; Yavari & Zaker, 2019).
- Retail demand, which is uncertain, has also been taken into account (Onggo et al., 2019; Wu et al., 2018)
- A four-tier supply chain consists of multiple suppliers, manufacturers, distribution centers and retailers optimized in this research (developed by the authors).
- Distribution centers play a mediating role in the transfer of various types of perishable products from manufacturing centers to retailers (developed by the authors).
- It is assumed that all transportation between supply chain nodes occurs using vehicles with limited capacity, and that route selection decisions are influenced by both transportation cost and emissions (Rafie-Majd et al., 2018).
- All the facilities in the production facility will have limited capacity (Bortolini et al., 2018; Govindan et al., 2014).
- The flow between two consecutive processes and the connection between the facility associated with a facilitator is not taking place (developed by the authors).
- Considering products with a specific and fixed lifespan (Shafiee et al., 2021).
- Considering different types of vehicles with different capacities (Tavakkoli Moghaddam et al., 2019).
- The model incorporates environmental taxes (e.g., NOx, CO2, HC, and CO penalties), potential disruptions in supply chain facilities (due to natural disasters or supply-side failures), and social indicators derived from expert consensus (developed by the authors).

Based on the assumptions defined, we now present the indices and parameters used in constructing the mathematical model. These elements capture the structural and operational characteristics of the perishable supply chain system.

3.2. Indices, parameters, and variables of the model: Indices, variables, and problem parameters are listed in Table 3.

Table 3. indices, Parameters and Variables

Indices	**t**	The time horizon t (considered to be 6 months)
	P	products $P = 1, 2, \ldots, p$
	S	supply centers $S = 1,2, \ldots, s$
	R	retail outlets $R = 1,2, \ldots., r$
	K	distribution centers $K = 1,2, \ldots, k$
	M	raw materials $M = 1,2, \ldots, m$
	I	routes $I = 1,2, \ldots., i$
	N	Products number $N = 1,2, \ldots, n$
	Z	Warehouses $\mathrm{Z} = 1,2 \ldots, z$
	F	Producers $\mathrm{F} = 1,2, \ldots, f$
	V	vehicles $V = 1,2, \ldots, v$
	D	Product price
	Y	Product lifespan
	A	Workers employed for up to 20 years of service
	B	Workers employed for up to 10 years of service

	C	Workers employed for up to 5 years of service
	d	Employee with less than 2 years of service
Economic parameters	$\boldsymbol{AR_{sf}}$	If the s supplier is available to supply s raw materials for the factory.
	XV_{sf}	Type v vehicle capacity
	CAP_s	Supply capacity of raw materials m by s supply centers
	MD_{krm}	The average demand for product m across k distribution centers and retailer r
	RHS_{sf}	Auxiliary variable for calculating the number of times of relocation of supply centers s and production center f
	TAB_p	Weight of each product p
	HI_{pf}	Processing time for the production of a unit of product p at the production center of f
	CAP_f	Annual production capacity of production center f
	CAP_k	Distribution center k holding capacity
	CAP_r	Holding capacity of retailer r
	$QDPN_{nr}$	Expected demand value of retail centers r for product p
	$QDPN_{nk}$	Predicted demand value of distribution centers k for product p
	$T\varepsilon'$	Taxes (percentage of fines) per unit of carbon emissions from production at the production center
	$T\beta$	Tax (percentage of penalties) per unit NOX emissions resulting from transportation (product or raw material) of vehicle v
	$T\alpha$	Taxation (percentage of fine) per unit of CO2 emissions from transport (product or raw material) of vehicle v
	$T\gamma$	Taxation (percentage of fine) per unit of HC emissions resulting from transportation (product or raw material) of the vehicle v
	$T\lambda$	Taxes (percentage of fines) per unit of CO emissions resulting from transportation (product or raw material) of vehicle v
	LQC_{pr}	Product cost p in retail centers r
	LQC_{pk}	Cost of crop waste p in distribution centers k
	ODN	Product type freshness priority (importance of product type relation)
	FCQ_r	The fixed cost associated with ordering from retailer centers r.
	FCQ_k	Fixed cost of ordering distribution centers k
	FCQ_f	Fixed cost of ordering production center f
	$XVTC_{pfk}$	Variable shipping cost per unit of product p from production center f to distribution centers k
	$XFTC_{pfk}$	Fixed shipping cost per unit of product p from production center f to distribution centers k
	$XVTC_{pkr}$	Variable cost of transportation per unit of product p from k distribution centers to retailers r
	$XFTC_{pkr}$	Fixed shipping cost per unit of product p from k distribution centers to retailers R
	$XVTC_{msf}$	Variable cost of transportation for each unit of raw materials m from supply centers s to production center f
	$XFTC_{msf}$	Fixed shipping cost per unit of raw material m from supply centers s to production center f
	XVP_p	Variable cost per unit of product p
	A	Lost cost per unit (caused by failure)
	N_{vt}	Number of vehicles v per period t
	π_{pr}	Unit sales cost missing product type p in Retailer r
	π_{pk}	Cost of selling unit missing product type p in distribution centers k
	π_{pf}	Cost of sales unit lost product type p in production center f
	θ_p	Inventory failure rate of product type p
	CD_f	Unmet (unexpected) demand cost of production center f
	CD_k	Unmet application fee of distribution center k
	CD_r	Retailer's unmet application fee r
	$\tilde{\omega}$	Fuel consumption costs
	FX_k	Fixed cost of opening of distribution center k
	HF_{mzft}	Maintenance cost of raw material m in stock z Production center f per period t
	FHK_{pzkt}	Product maintenance cost p in warehouse z distribution centers k per period t
	HF_{pzrt}	Product maintenance cost p in warehouse z retailers r per period t
	VI_{pzkt}	Variable cost in distribution units
	PUR_{pfdt}	Cost of purchasing unit of product p from production center f at price level d at time t
	PUR_{pkdt}	Cost of purchasing unit of product p from distribution centers k at price level d in time t
	PUR_{psdt}	Cost of purchasing raw materials p from supply centers at the price level d in the time frame t
	$\alpha' n$	The percentage of product waste n produced by the manufacturer
	RHS_{fk}	Auxiliary variable for calculating the number of times of movement of production centers f and distribution centers k
	RHS_{kr}	Auxiliary variable for calculating the number of relocations of k distribution centers and retailers r

	XFV_{vsf}	V-type vehicle capacity to transport raw materials from supply center s to production center f
	XFV_{vfk}	V-type vehicle capacity to carry product from production center f to k distribution centers
	XFV_{vkr}	V-type vehicle capacity to carry the product from to k distribution centers to retailer r
	DE_{sf}	Transportation distance from supplier s to production center f
	DE_{fk}	Transportation distance from production center f to distribution center k
	DE_{kr}	Transportation distance from k distribution center to retailer r
	ASR	Number of raw material transfers between suppliers and manufacturers
	ARP	Number of products moving between producers and distribution centers
	ARR	Number of products moving between distribution centers and retailers
	ETH	Environmental rate of producer's emission
	$ET\gamma_{vsf}$	Emissions of HC per unit for transporting with vehicle v of cargo from the supply centers of s to the production center of f
	$ET\lambda_{vsf}$	Amount of CO for vehicle v transport per unit of cargo from the supply centers s to the production center f
	$ET\beta_{vsf}$	NOX emission per unit of load per unit of transport by vehicle of v for every unit from supply center s to production center f
	$ET\alpha_{vsf}$	CO2 emission per unit of load per unit of transport by vehicle of v from the supply center s of production center f
	$ET\gamma_{vfk}$	The amount of HC per unit of transport by v per unit of load from the production center f to the distribution centers k
	$ET\lambda_{vfk}$	Amount of CO for transport by vehicle v per unit of load from the production center f to distribution centers k
	$ET\beta_{vfk}$	NOX emission per unit of freight from production center f to distribution centers k
	$ET\alpha_{vfk}$	CO2 emission per unit of transport by v per unit of cargo from production center f to distribution centers k
	$ET\gamma_{vkr}$	HC emissions per unit of transport by v per unit of cargo from k distribution centers to retailer r
	$ET\lambda_{vkr}$	CO emissions per vehicle v transport per unit of cargo from distribution centers k to retailer r
	$ET\beta_{vkr}$	NOX emissions per vehicle v transport per unit of cargo from k distribution centers to retailer r
	$ET\alpha_{vkr}$	CO2 emissions per vehicle transport by vehicle v per unit of cargo from distribution centers k to retailer r
	$ET\gamma_{vkf}$	Emissions of HC per unit of load per unit of transport with vehicle v from k distribution centers to production center f
	$ET\lambda_{vkf}$	CO emissions per vehicle v transport per unit of cargo from distribution centers k to production center f
	$ET\beta_{vkf}$	NOX emission per unit of load from distribution with vehicle v from centers k to production center f
	$ET\alpha_{vkf}$	Emission per unit of transport by vehicle v per unit of cargo from distribution centers k to production center f
	$ET\varepsilon'$	Carbon emissions per product at the manufacturing center
Social Parameters	$\boldsymbol{CEN_a}$	Salary of each worker up to 20 years of service in each period t
	CEN_b	Salary of each worker up to 10 years of service in each period t
	CEN_c	Employee salary up to 5 years of service in each period t
	CEN_d	Salary of every worker working under 2 years of service in each period t
	CHN	Cost of hiring a worker each period t
	CFN	Worker's unemployment cost due to Covid every period t
	CED_f	Cost per hour of staff training employed by production center f in period t
	CED_s	Cost per hour of staff training recruited at the supply centers in period t
	CRA	The average cost of each road accident relates to each level of the supply chain.
	$Ceni$	Weight related to each of the social effects
	$ACSE_f$	Average cost of purchasing safety equipment at production center f during period t
	$ACSE_s$	Average cost of purchasing safety equipment at supply centers s in period t
	$ACSE_k$	Average cost of purchasing safety equipment in distribution centers k during period t
	$ACSE_r$	The average cost of purchasing safety equipment at the production center during the period t
	ACk	The average cost of accidents caused by non-compliance with safety in distribution centers k in period t
	$INNR$	Average costs paid for the design and equipment of new products in the production center f in period t
	SA_f	Percentage of personnel absenteeism due to lack of dissatisfaction with the work environment for production center f during period t
	SA_s	Percentage of personnel absenteeism due to lack of dissatisfaction with the work environment for supply centers s in the time period t
	SA_k	Percentage of personnel absenteeism due to lack of dissatisfaction with the work environment for distribution centers k in the time period t

	DRT	The number of days lost due to Covid in the workplace
	UP_{kt}	Unemployment rate in distribution centers k during period t
	UP_{ft}	Unemployment in the production center of, f during the time period t
	αF	Demand response weight factor
	pb	Late cost on order delivery
	$COHN_t$	The cost of laying off employees due to coronavirus
	ET	Weight coefficient for components of social purpose function
	ACS_s	Costs of accidents occurred at the s supply centers
	ACS_f	The cost of accidents occurred at the production center of f
	ACS_k	Cost of accidents occurred at distribution centers k
	ACS_r	Cost of accidents occurred at retail centers r
Other Parameters	α'	Coefficient of use of raw materials
	M	A large number

$\boldsymbol{\omega_{pfkvt}}$	The quantity of purchased product p (or gross order quantity of distribution center) from production center f to distribution centers k by vehicle type v within the time interval t
$\boldsymbol{\omega_{pkrvt}}$	The quantity of purchased product p (or gross order value of retailer) from distribution centers k to retailer by vehicle type v in the time interval t
$\boldsymbol{\omega_{msfvt}}$	The amount of raw material purchased m (or gross order quantity of production center) from supply centers to production center f by vehicle type v within the time interval t
$\boldsymbol{SK}$	If the distribution center k is opened 1 otherwise zero
$\boldsymbol{QPN'}$	Total product quantity QPN^'
$\boldsymbol{\xi_v}$	The amount of fuel consumed by the type of vehicle v per unit distance
$\boldsymbol{\varphi_{vsft}}$	If the vehicle v travels from supplier s to production center f in time period t, an otherwise zero
$\boldsymbol{\varphi_{vfkt}}$	If the vehicle v travels from production center f to distribution center k in time period t, then it would be one, otherwise be zero
$\boldsymbol{\theta_{vkrt}}$	If vehicle type v travels from distribution center k to retailer r in period t, one otherwise zero
$\boldsymbol{US_s}$	Number of purchases from supply centers s
$\boldsymbol{US_k}$	The number of purchases from distribution centers k
$\boldsymbol{US_f}$	Number of purchases from the production center f
$\boldsymbol{IF_{pzft}}$	Product inventory level p in warehouse z production center f at the beginning of the year period t = 1
$\boldsymbol{Ik_{pzkt}}$	Inventory level p warehouse z distribution centers k at the beginning of the year period t = 1
$\boldsymbol{Ir_{pzrt}}$	Product inventory level p warehouse z retailers r at the beginning of the year period t = 1
$\boldsymbol{ISM}$	Raw material inventory level in stock z production center f at the beginning of the year period t = 1
$\boldsymbol{QPN_{mtsf}}$	Product quantity m sent in period t from supply centers s to production center f under scenario s
$\boldsymbol{QPN_{ptfk}}$	The quantity of product p sent in period t from production center f to distribution centers k under scenario s
$\boldsymbol{QPN_{ptkr}}$	The quantity of product p sent in period t from distribution centers k to r retailers under scenario s
$\boldsymbol{QPN_{ptrk}}$	Quantity of product p returned due to being expired in period t from retailers r to distribution centers k under scenario s
$\boldsymbol{QPN_{ptkf}}$	The amount of product p returned due to expire in period t from distribution centers k to production center f under scenario s
$\boldsymbol{WF_r}$	The amount of goods returned due to the failure of retailer centers r
$\boldsymbol{QD_f}$	Unmet demand of production center f
$\boldsymbol{QD_k}$	Unmet demand of distribution centers k
$\boldsymbol{QD_r}$	Unmet demand amount of retailer centers r
$\boldsymbol{HNT_S}$	The percentage of workers employed by the supply centers during the period t
$\boldsymbol{HNT_F}$	Percentage of workers employed at the production center of f during the period t
$\boldsymbol{HNT_K}$	Percentage of workers employed at distribution centers k during the period t
$\boldsymbol{ENT_a}$	Percentage of workers working for up to 20 years in each period t
$\boldsymbol{ENT_b}$	Percentage of employees up to 10 years of service in each period t
$\boldsymbol{ENT_c}$	Percentage of employees up to 5 years of service in each period t
$\boldsymbol{ENT_d}$	Percentage of workers working under the year of service in each period t
$\boldsymbol{UENT_s}$	Percentage of workers unemployed by the covid in each period t
$\boldsymbol{UENT_f}$	Percentage of workers unemployed by the covid disease at the production center of the f in each period t
$\boldsymbol{UENT_k}$	Percentage of workers unemployed due to the covid in K-distribution centers in each period t
$\boldsymbol{NED_s}$	The number of staff trained in the production center f in the time period t
$\boldsymbol{NED_k}$	Number of trained staff in distribution centers k during the time period t
$\boldsymbol{NAC_f}$	The number of accidents caused by non-compliance with safety or lack of safety equipment at the production center f during the time period t

NAC_k	The number of accidents caused by non-compliance with safety or lack of safety equipment in distribution centers k during the time period t
NAC_r	The number of accidents caused by non-compliance with safety or lack of safety equipment in retail centers in the time period t
NAC_s	The number of accidents caused by non-compliance with safety or lack of safety equipment in the supply centers during the time period t
NSE_s	The number of safety equipment purchased in the supply centers during the time period t
NSE_k	The number of safety equipment purchased at distribution centers k during the time period t
NSE_r	The number of safety equipment purchased at the production facility f during the time period t
NSE_r	The number of safety equipment purchased in retail centers in the period t
NSA_f	Number of personnel complaints due to dissatisfaction of the environment of production center f in the time period t
NSA_f	Number of personnel complaints due to dissatisfaction of the environment of distribution centers k in the time period t
NSA_s	The number of personnel complaints due to lack of satisfaction in the environment of supply centers during the time period t
DQP_f	Quantity of demand from production centers f
DQP_s	Demand from supply centers s
DQP_r	Quantity of demand from sales centers r
Do_{tn}	Time to send order
RI	Order request time
JCW_k	Number of job openings if distribution centers of k are opened with a level of capacity n
JCW_f	The number of job openings created if the production center f is produced with a capacity level n
FRI	Freshness level of orders (distribution, production, supply) in delivery
SKO_{ktr}	If the distribution center of k serves the retailer r at the time of t, one and otherwise zero
SKO_{kmtf}	If the distribution center of k is assigned to the factory within the time interval t for product m one, otherwise zero
PL_{pvt}t	The number of pallets suitable for the carriage of product p by vehicle v in the time period t
BQ_{sf}	Binary variable if raw materials are sent from supply centers to production center
BQ_{fk}	Binary variable if the quantity of product p is sent from production center f to distribution centers k
BQ_{kr}	Binary variable if the quantity of product p is sent from distribution centers k to retailer's r

Based on Eq. 1, the first objective function is formulated. Fuel consumption, purchases, unmet demand, ordering costs, expiration, product downtime, social (including hiring, firing, and the cost of firing due to a coronavirus), transportation and environmental costs, the creation of a distribution center, lower maintenance costs, and maximizing product freshness are the components of this model. The economic goal is to minimize the function of the goal. The second objective function based on Eq. 2 is to reduce emissions of environmental pollutants such as NOx CO, HC CO2 through the reduction of return goods and fuel consumption caused by significant transportation of vehicles. It looks into fuel usage as well and gets smaller the more items that are returned. The third objective function is related to the social dimension of supply chain sustainability. The components of the third objective function based on Eq. 3 (social indicators of job satisfaction) are security that the social goal in this model is to maximize the goal function and on the other hand, minimizing risks and accidents is considered to reduce lost days.

$$
\begin{aligned}
MinF_1 = {} & \tilde{\omega} \sum_{s} \sum_{f} \sum_{k} \sum_{r} \varepsilon_v . \varphi_{vsfkr} DE_{sfkr} \\
& + \sum_{s} \sum_{f} \sum_{k} \sum_{r} \xi_v . DE_{sfkr} \\
& + \sum_{s} \sum_{f} \sum_{k} PUR_{sfk} . \omega_{sfk} \\
& + \sum_{f} \sum_{k} \sum_{r} FCQ_{fkr} . US_{fkr} \\
& + \sum_{f} \sum_{k} \sum_{r} CD_{fkr} . QD_{fkr} \\
& + \sum_{f} \sum_{k} \sum_{r} LQC_{fkr} . \pi_{fkr} \\
& + \sum_{f} \sum_{k} \sum_{r} CEN_{abcd} . ENT \\
& + \sum_{s} \sum_{f} \sum_{k} CHN . HNT_S \\
& + \sum_{s} \sum_{f} \sum_{k} COHN_t \, UENT_t \\
& + \sum_{s} \sum_{f} \sum_{k} UENT_{sfk} . CFN + [\sum_{k} \sum_{r} A . WF_{kr} \\
& + N_{vt} \sum_{s} \sum_{f} \sum_{k} \sum_{r} [(QPN_{ptsfkr} . XVTC_{sfkr}) \\
& + XFTC_{sfkr}] + [SK . (QPN_{ptfk} . XVTC_{pk}) + XFTC_{pk}] \\
& + \sum_{s} \sum_{f} \sum_{k} \omega . T\beta . T\lambda . T\gamma . T\alpha + ET\varepsilon' . T\varepsilon' QPN' \\
& + SK . T\beta . T\gamma . T\lambda . T\alpha . \omega_{pfkv} + FX_k . SK \\
& + \tilde{\omega} . \varphi_v . De . sk . \xi_v + HR_{pzrt} . IR_{pzkt} + IK_{pzkt} \\
& + (HK_{pzkt} + VI_{pzkt}) + HF_{pzft} . ISM \\
& - \sum_{s} \sum_{f} \sum_{k} FRI . QP\acute{N}_n \\
& + \sum_{f} \sum_{k} \sum_{r} ODN . FRI . DQP_{fkr}
\end{aligned}
\tag{1}
$$

$$
\begin{aligned}
MinF_2 = {} & \sum_{s} \sum_{f} \sum_{k} \omega . WF_{kr} . LQC_{fkr} \\
& + \sum_{\alpha} \sum_{\beta} \sum_{\lambda} \sum_{\gamma} ASR . \omega_{psfv} . DE_{sf} . ET_{\alpha\beta\lambda\gamma} \\
& + \sum_{\alpha} \sum_{\beta} \sum_{\lambda} \sum_{\gamma} ARP . \omega_{pfkv} . DE_{fk} . ET_{\alpha\beta\lambda\gamma} \\
& + \sum_{\alpha} \sum_{\beta} \sum_{\lambda} \sum_{\gamma} ARR . \omega_{pkrv} . DE_{kr} . ET_{\alpha\beta\lambda\gamma}
\end{aligned}
\tag{2}
$$

$$
\begin{aligned}
MaxF_3 = {} & \sum_{s} \sum_{f} \sum_{k} ceni . SA . NSA + \sum_{s} \sum_{f} \sum_{k} \sum_{r} ceni . NSE . ACSE \\
& + \sum_{f} \sum_{k} ceni . NDEF . NED + Sk \sum_{f} \sum_{k} JCW . UP \\
& - \sum_{f} \sum_{k} pb \, [F\alpha \sum_{f} \sum_{k} \omega_{pv} + (1 \\
& - F\alpha) \sum_{f} \sum_{k} WF] \\
& + \sum_{s}^{i} \sum_{f}^{j} \sum_{k}^{k} \sum_{r}^{r} DO_{tn} . DQP_r (DO_{tn} - RI) \\
& + \sum_{s}^{r} \sum_{f}^{f} \sum_{k}^{k} \sum_{r}^{r} ceni . ACS . NAC \\
& + \sum_{s} \sum_{f} \sum_{k} \sum_{r} ceni . CRA . (ASR + ARP + ARR) \\
& + ET \sum_{s} \sum_{f} \sum_{k} \sum_{r} DRT . QPN
\end{aligned}
\tag{3}
$$

The given model includes the following constraints:

$$\sum_{\alpha}\sum_{\beta}\sum_{\lambda}\sum_{\gamma} ET_{vsf}.\,\omega_{psfv}\,.\,BQ_{sf} \leq \sum ET\alpha\beta\lambda\gamma \tag{4}$$

$$\sum_{\alpha}\sum_{\beta}\sum_{\lambda}\sum_{\gamma} ET_{vfk}.\,\omega_{pkfv}\,.\,BQ_{fk} \leq \sum ET\alpha\beta\lambda\gamma \tag{5}$$

$$\sum_{\alpha}\sum_{\beta}\sum_{\lambda}\sum_{\gamma} ET_{vkr}.\,\omega_{pkrv}\,.\,BQ_{kr} \leq \sum ET\alpha\beta\lambda\gamma \tag{6}$$

$$\sum_{f}\sum_{k}\sum_{r} XV_{vfk} - 1 \leq \sum_{f}\sum_{k}\sum_{r} XV_{vfk} \leq \sum_{f}\sum_{k}\sum_{r} XV_{vfk} \tag{7}$$

$$\sum SK \leq 1 \tag{8}$$

$$QPN'_{n} \geq QPN'_{n} - QPN'_{n}.\alpha' \tag{9}$$

$$QPN'_{n} - QPN'_{n}.\alpha' n \geq \sum_{k}\sum_{r} QPN_{pt} - \sum_{k}\sum_{r} \theta_{p} \tag{10}$$

$$HI_{pf} \cdot QPN_{ptfk} \leq \sum_{k} CAP_{k}.SK \tag{11}$$

$$HI_{pf} \cdot QPN_{ptfk} \leq \sum_{f}\sum_{k}\sum_{r} CAP_{fkr} \tag{12}$$

$$\sum_{f} AR_{sf} \leq (1 - a_{k}^{s})CAP_{s} \tag{13}$$

$$\mathrm{QDPN_{rp}} + \mathrm{QDPN_{kp}} = \left[\left(\omega_{\mathrm{p.st.kvt}} + \omega_{\mathrm{p.k.rv}}\right) - (\mathrm{WF_{k}} + \mathrm{WF_{r}})\right] \tag{14}$$

$$\mathrm{IF}_{pzf} + \sum_{k}\sum_{r} \omega_{Pfkv} = \sum_{k}\sum_{r} QPN_{ptkr} \cdot SKO_{ktr} \tag{15}$$

$$\sum_{k}\sum_{r} \omega_{Pv} \leq \sum_{k}\sum_{r} CAP_{kr} \cdot SK \tag{16}$$

$$\sum_{f}\sum_{k}\sum_{r} \omega_{pv} \leq \sum_{f}\sum_{k}\sum_{r} XV_{v} \tag{17}$$

$$\sum_{f}\sum_{k}\sum_{r} DQP_{fkr} \cdot \varphi_{v} \leq XV_{v} \cdot VF_{ij} \tag{18}$$

$$SKO_{tr} \leq 1 \tag{19}$$

$$\theta_{vkrt} \leq 1 \tag{20}$$

$$QPN_{ptfk} \cdot SKO_{kmtf} \geq \sum_{k} MD_{krm} SKO_{tr} \tag{21}$$

$$QPN_{ptfk} \geq \sum_{k} \omega_{Pkrvt} \tag{22}$$

$$QPN'_{n} - QPN'_{n}.\alpha' n \geq \sum_{k}\sum_{r} MD_{krm}\,.\,\mathrm{SKO_{tr}} \tag{23}$$

$$\sum_{k}\sum_{r} MD_{krm}\,.\,\mathrm{SKO_{tr}} \leq \mathrm{SK} \cdot \mathrm{CAP_{k}} \tag{24}$$

$$\mathrm{QPN'_{n}} = \sum_{n}^{r} \mathrm{QDPN_{nr}} + \mathrm{QDPN_{nk}} - (\mathrm{QD_{f}} + \mathrm{QD_{k}}) \tag{25}$$

$$\mathrm{QPN'_{n}} \geq \sum_{r} \mathrm{QDPN_{nr}} - \mathrm{QD_{r}} \tag{26}$$

$$\sum_{s} \mathrm{QPN_{ptsf}} \leq \mathrm{CAP_{s}} \tag{27}$$

$$\frac{\sum_{f} QPN_{ptsf}}{XV_{v}} + RHS_{sf} = ASR \tag{28}$$

$$\frac{\sum_{k} QPN_{ptfk}}{XV_{v}} + RHS_{fk} = ASP \tag{29}$$

$$\frac{\sum_{r} QPN_{ptkr}}{XV_{v}} + RHS_{kr} = ARR \tag{30}$$

$$ASR + RHS_{sf} \geq 0 \tag{31}$$

$$ASp + RHS_{fk} \geq 0 \tag{32}$$

$$ASR + RHS_{kr} \geq 0 \tag{33}$$

$$\sum_{f}\sum_{k}\sum_{r} QPN_{ptsf} = \sum_{f}\sum_{k}\sum_{r} DQP_{Skr} \tag{34}$$

$$\sum_{k} SK = 1 \tag{35}$$

$$SKO_{ktr} \leq SK \tag{36}$$

$$SKO_{ktr} \leq QPN_{ptkr} \leq SKO_{ktr} \cdot M \tag{37}$$

$$ISM_{t} = ISM_{t-1} + \sum_{f} \omega_{pskv} - \sum_{f} \alpha' \cdot QPN'_{n} \tag{38}$$

$$IF_{zpzf,t} = (1-\theta_p)IF_{pzf,t-1} + QPN'_n - \sum_f QPN_{ptfk} \tag{39}$$

$$Ik_{pzk} = Ik_{pzk,t-1} + \sum_f \omega_{Pfkvt} - \sum_k QPN_{ptkr} \tag{40}$$

$$\sum_f\sum_k\sum_r DQP_{fkr} - \sum_f\sum_k\sum_r \omega_{Pfkvt} - \sum_f\sum_k\sum_r WF = \sum_f\sum_k\sum_r QD_{fkr} \tag{41}$$

$$\sum_f\sum_k\sum_r \omega_{pv} \le \sum_f\sum_k\sum_r \varphi_v . \sum_f\sum_k\sum_r XVM_{vm} \tag{42}$$

$$\sum_s\sum_f\sum_k\sum_r Ii^{t.y-1} \le \sum_s\sum_f\sum_k\sum_r Ii^y \tag{43}$$

$$\sum_f\sum_k\sum_r (XFTC_{fkr} + XFTC_{fkr}) . (1 - Ii_r^y) \le \sum_f\sum_k\sum_r (\mathrm{Ir}_{pzrt} + \omega_{pkrv}) - QPN_{ptkr} + 1 \tag{44}$$

$$QPN_{ptrk} = 0 \tag{45}$$

$$QPN_{ptkf} = 0 \tag{46}$$

$$QPN_{ptkf} + QPN_{ptrk} \le B_j . \sum_k\sum_r QPN_{pt} \tag{47}$$

$$\sum_S\sum_F\sum_K ENT_{abcd} . SA \le \sum_s\sum_f\sum_k ENT_{abcd} \tag{48}$$

$$Ii_r^y, Ii_f^y, Ii_s^y, \varphi_{vk.r}, \varphi_{vfk}, \varphi_{vsf}, SKO_{ktr}, SKO_{kmtf}, SK, SR, VF_{i.j}, \theta_{vkrt}, \theta_{vfkt}, \theta_{vsft}, BQ_{sf}, BQ_{fk}, BQ_{kr}, \tag{49}$$

$$Ii_r^y, Ii_f^y, Ii_s^y, \varphi_{vk.r}, \varphi_{vfk}, \varphi_{vsf}, SKO_{ktr}, SKO_{kmtf}, SK, SR, VF_{i.j}, \theta_{vkrt}, \theta_{vfkt}, \theta_{vsft}, BQ_{sf}, BQ_{fk}, BQ_{kr}, ASP, ARR, RHS_{s.f}, RHS_{fk}, RHS_{kr}, XV_v, CAP_s, QDR_i, QDPN_{ns}, QDPN_{n,r}, QDPN_{n,k}, Qdfac, Qdk_i, Cap_k, \omega_{Pfkvt}, \omega_{p.k.rv}, \omega_{P.f,k,v}, MD_{krm}, XV_{vkr}, XV_{vfk}, XV_{vsf}, Ifac_{pzf}, CAP, Hi_{pf}, \alpha_k^s, PL_{pvt}, TAB_p, HN_t, UEN_t, BQ_{k.s}, \theta_P, ET\lambda, ET\beta, ET\alpha, ET\alpha_{ks} ET\beta_{ks}, ET\gamma_{ks}, ET\alpha_{ks}, ET\gamma, ET\lambda_{fk}, ET\beta_{fk}, ET\gamma_{fk}, ET\alpha_{fk}, ET\lambda_{sf}, ET\beta_{sf}, ET\gamma_{sf}, ET\alpha_{sf}\ Ik_{pzk}, QPN_{ptfk}, QPN_{ptkr}, QPN_{ptsf}, QPN_{ptrk}, \alpha', ISM_t\ QPN'_n, DQP_S, DQP_k, DQP_r, ASR \ge 0 \tag{50}$$

The provided equations, from 4 to 7, outline the emissions of various pollutants, such as CO2, NOx, C, and HC. Equation 8 calculates the sum of product orders p transmitted by vehicle type v in period t, which is then divided by the weight of the product type p to determine the number of vehicles of type v required to transport the products p in period t. Equation 9 guarantees that a distribution center cannot be situated at a location that exceeds its capacity. Equations 10 and 11 establish the flow balance constraint in production centers, distribution centers, and retail stores. Equations 12 and 14 represent the capacity limitations of suppliers, production centers, and distribution centers. Equation 15 states that the quantity of demand for distribution and retail centers is equal to the amount of goods sent to those centers, adjusted for the fraction of estimated demand and the quantity of expired products. Equation 16 governs the inventory balances in distribution centers and retail stores.

The stipulations outlined in equation 17 indicate that the volume of products dispatched to retail and distribution centers must align with their designated capacities. Equation 18 delineates the capacity parameters for each vehicle, while equation 19 ensures that these capacities are adequately adjusted to meet transportation demands. Furthermore, equation 20 specifies that each retailer is to receive supplies exclusively from a single distribution center, and equation 21 guarantees that each retailer is serviced by the distributor only once. Equation 22 affirms that the average demand for distribution centers across all product lines is satisfied. In addition, equation 23 asserts that the output of each product from the distribution center must not exceed the input received by that center. Equation 24 is concerned with ensuring that the average customer demand is fulfilled. Lastly, equation 25 encapsulates the capacity limitations applicable to both distribution and retail centers.

Equations 26 and 27 delineate the equilibrium of demand, signifying that the demand for product M from the retailer corresponds to the aggregate of items dispatched from all distribution centers to the retail hub. Equation 28 asserts that the procurement from each supplier must remain within its designated capacity limits. Equations 29 through 34 quantify the frequency of movements among supply centers, manufacturing facilities, distribution centers, and retailers for the transportation of products and raw materials. Equations 35 and 36 assert that the demand at each level of the supply chain for every product during each time period must be completely satisfied within that same period. Equation 37 clarifies that a distribution center may only serve customers if it has been constructed. Equation 38 demonstrates that products can flow from a distribution center to a customer only if that distribution center is allocated to the customer. Equation 39 is derived from the equilibrium equations concerning raw materials at the production center. Equations 40 and 41 guarantee that the quantities of product types in both the production center and distribution centers are consistent across each period. Finally, equation 42 highlights the unmet demands present in retail, distribution, and production centers.

Equation 43 indicates that the auxiliary variable representing the product life of product $y-1$ assumes a value of one if the auxiliary variable for the product with a life of y is equal to one. This implies that the inventory of product life $y-1$ is utilized to satisfy demand when the inventory of product life y is inadequate. Equation 44 serves to ensure that all quantitative variables do not attain a value of one, stipulating that if the available inventory does not employ the life of product $y-1$ to fulfill demand, the positivity constraint on the right-hand side results in the auxiliary variables for product $y-1$ being zero. Equations 45 and 46 assert that during the period preceding the product's lifetime, no products are transferred from retailers to distribution centers or from distribution centers to production centers. Equation 47 addresses the return of expired products to both distribution and manufacturing centers. Equation 48 specifies that the number of employees terminated in period t must be fewer than the number of employees hired. Finally, Equations 49 and 50 also delineate variables that are constrained to zero and one, as well as non-negative variables.

4 RESULTS AND DISCUSSION: In this study, the models underlying presumption, which were derived from the characteristics of perishable products in the dairy and pharmaceutical industries, are taken into account. Subsequently, the model underwent validation, and twelve distinct problems were formulated to assess the efficacy of the proposed model. These problems were analyzed using experimental data and were resolved with the aid of GAMS software and the CPLEX solver. Then, the values related to the parameters of the pharmaceutical and dairy company were collected. In the next step, validation of the proposed model was evaluated and analyzed using the NSGAII meta-heuristic algorithm.

As mentioned, to solve the proposed multi-objective model, the modified ε-constraint method was applied. This method transforms a multi-objective optimization problem into a single-objective problem by optimizing one objective function while converting others into constraints bounded by a series of predefined epsilon values. The approach used in this study involves a grid-based ε-segmentation technique that generates Pareto-optimal solutions across the objectives by systematically varying these bounds. This method is particularly useful for exploring trade-offs between objectives and was employed to generate a representative set of efficient solutions for comparative analysis. Here is the set of optimal Pareto solutions according to Table 3. "OF" stands for "objective function." OF 1, OF 2, and OF 3 represent the economic, environmental, and social sustainability objectives, respectively, as defined earlier in equations (1), (2), and (3).

Table 3. Optimal pareto solutions

ε	First OF	Second OF	Third OF
1909.00	24759	1939	12418
3793.00	45314	3831	15436
5677.00	65564	5686	16512
7561.00	87119	7578	21619
9445.00	13029	9459	22546
11329.00	17525	11344	24812
13213.00	24679	13234	24919
15097.00	31833	15125	25512
16981.00	39456	16990	25396
18873.00	48143	18881	25659

The Pareto diagram is also found in Figure 1.

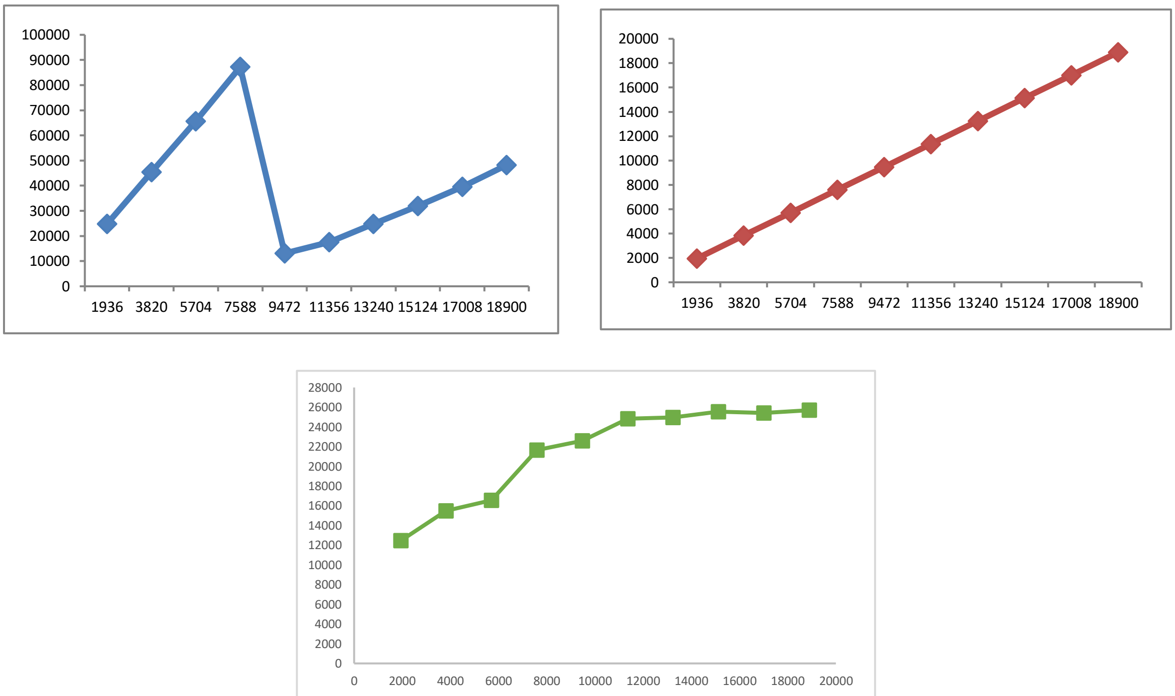

Figure 1. The ratio epsilon values in three objective functions

As is evident, the ratio of the first objective function to the values of epsilon has shown that, in the first objective function, the breakdown effect has occurred in the optimization process, and according to the analysis done in this dimension, it has been shown that in this dimension the optimal profit has been reduced, and the second and third objective functions have the same trend in accordance with the increase of epsilon values. Hence, the Pareto front of the optimal solutions presented in Figure 2.

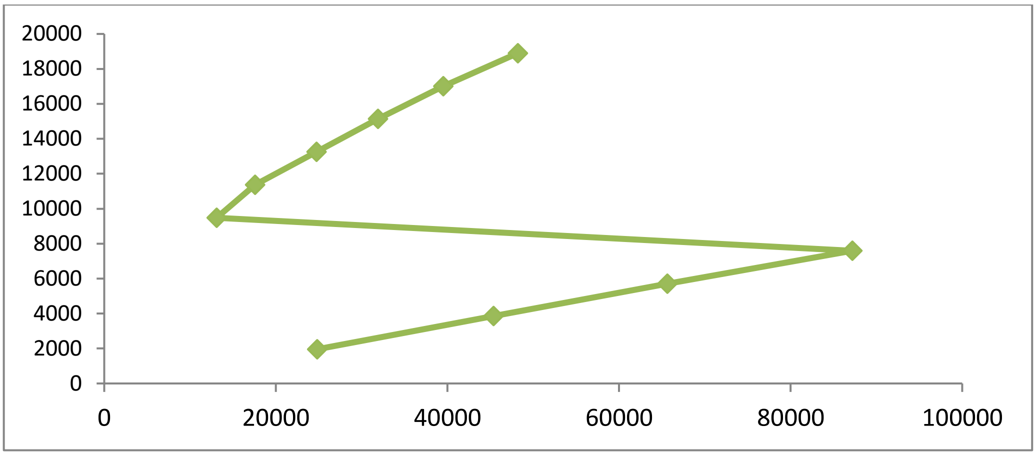

Figure 2. Pareto fronts optimal solution of the mathematical model

Following, the decision variables of the model were analyzed. The resulting values for the variable Ik_{pzkt} illustrate the level of inventory of the distributors in each time period, which is trending up until the first 3 periods of these values and progressively decreases after the fourth period. This is due to the fact that we only have production in the first three periods. The result of solving the integrated objective function model is the response to the first objective function (Z1), as seen in the sensitivity analysis of model stability versus stability in Figure 3. As predicted, a rise in ω causes Z1 to rise; however, the slope of this decline will eventually steepen.

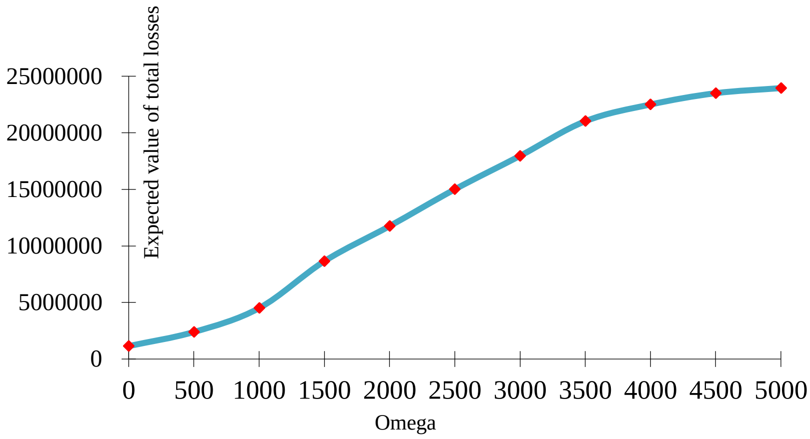

Figure 3. The association between Z_1 value from the integrated objective function

In comparing the current supply chain to the one suggested in Table 4, we see that operating expenses for 9 have decreased by 20% in the current supply chain. The environmental impact has been improved by nearly 20 times at the same time, and the level of service provided to employees has also improved. The comparisons demonstrate that the network developed for various performance objectives was resilient. The results pertaining to the combined method, in relation to the three objective functions established for the primary model, are summarized in Table 4.

Table 4. Objective function components for ten iterations

Repetition	T otal cost	Emissions Costs	Shipping cost	Cost of Employment	Cost of Social Indicators
1	922805	263960	155490	18136	424179
2	945580	242290	154800	15764	408224
3	963829.4	246500	157030	7230	423961

Repetition	T otal cost	Emissions Costs	Shipping cost	Cost of Employment	Cost of Social Indicators
4	944579	253110	152061	2975	407804
5	968527	252900	154831	21878	411730
6	967735	244840	156351	15764	423201
7	958540	251140	155031	13684	411634
8	945948	242830	154181	4049	418470
9	934048	239610	150341	8882	408956
10	981056	251920	157851	23817	419072
Expected value	960264.7	248910	154797	13218	417527
Standard deviation	18211.31	7178.28	2235.45	7213.92	6760.77

Repetition 1's results give us better answers than those from previous iterations, as Table 5 illustrates.

Table 5. Results of the main model objectives based on each repetition

Repetition	OF 1	OF 2	OF 3
1	1.3438e+14	1.1292e+11	9.2604e+09
2	3.7610e+14	3.4441e+11	5.6963e+09
3	3.7399e+14	3.4251e+11	5.7955e+09
4	3.7570e+14	3.4357e+11	5.7742e+09
5	3.7495e+14	3.4303e+11	5.6723e+09
6	3.7550e+14	3.4394e+11	5.6812e+09
7	3.7652e+14	3.4473e+11	5.7443e+09
8	3.7499e+14	3.4343e+11	5.7880e+09
9	3.7441e+14	3.4221e+11	5.6980e+09

The evaluation and analysis of the NSGA II algorithm has been conducted in accordance with the suggested mathematical model. The NSGA-II algorithm is characterized by several key features that facilitate the resolution of multi-objective optimization challenges. One notable aspect is the introduction of swarm distance as a substitute for traditional techniques like fitness sharing, which employs the binary tournament selection operator. This approach also incorporates the caching and archiving of non-dominated solutions derived from earlier phases of the algorithm. The non-dominated solutions, which emerge from addressing the multi-objective optimization problem, are referred to as the Pareto front. In the context of this research, two parent chromosomes were merged to create two offspring chromosomes through the application of simulated binary crossover operations.

To evaluate and ascertain the precision of the coding executed in MATLAB software, a small-scale sample problem is formulated for the proposed algorithms, and the output variables from the initial effective solution of the algorithm are presented. Consequently, the problem size is established during the preliminary validation, utilizing randomly generated parameters derived from a uniform distribution. Following this, the design problem is addressed using meta-heuristic algorithms of over 100 iterations, and the comparative indices of multi-objective meta-heuristic algorithms for each method are identified. Table 6 displays the mean values and indices of the results obtained from the application of the NSGA II and epsilon constraint algorithms.

Table 6. Comparative indicators of NSGA -II and modified epsilon constraint

Index	NSGA -II	Modified Epsilon
Computational Time	18.88	46.48
Average First Objective Function	413964.32	369883.17
Average Second Objective Function	68622.13	67371.28
Average Third Objective Function	63285.47	61478.29
NPS (Number of Pareto Answers)	10	9
RNI (Dispersion of Answers)	46646.39	49751.28
SA(Variance)	0.478	0.381

According to Table 6, the computational time required to solve the sample problem using the epsilon algorithm is less extensive compared to that of the NSGA II. Furthermore, NSGA II demonstrated superior performance relative to the epsilon constraint in identifying the number of efficient solutions. Also, according to the solving result, Figure 4 has been achieved by epsilon constraint and NSGAII algorithms.

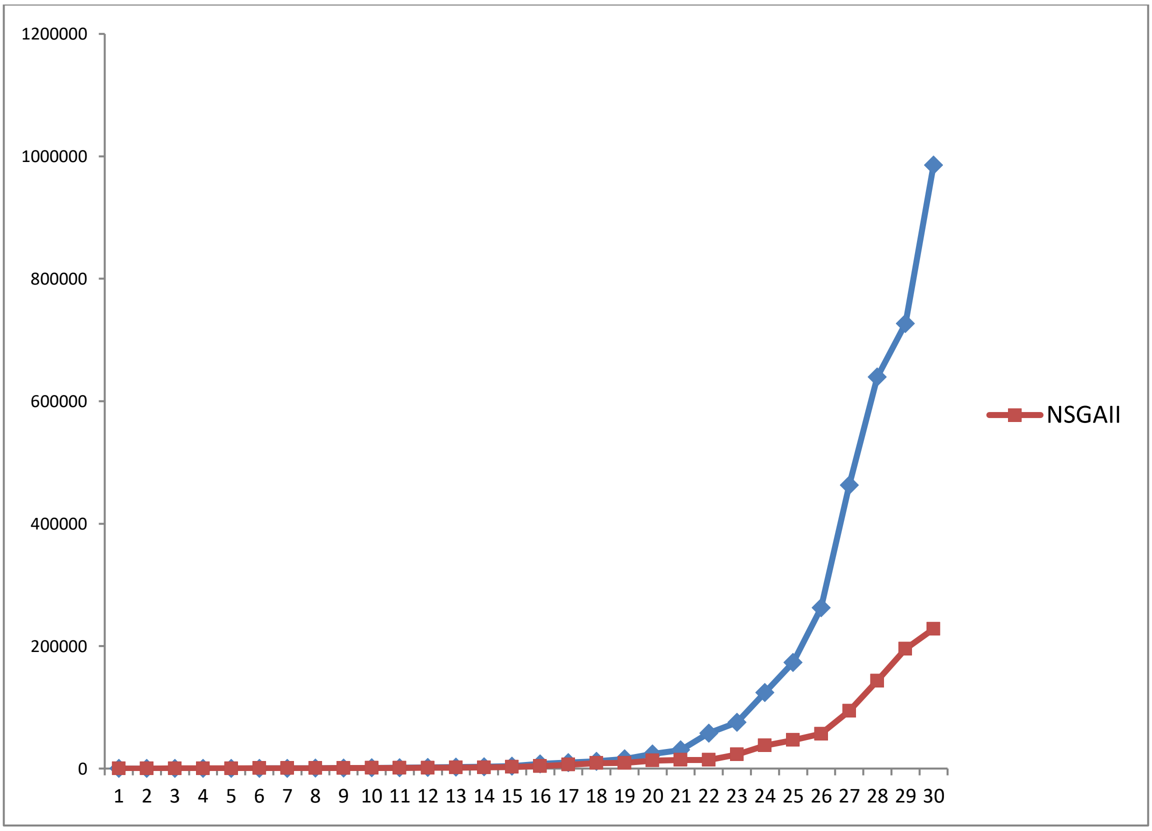

Figure 4. Result of solving the epsilon constraint and NSGAII

As it is stated, the solution time of the epsilon constraint algorithm in large dimensions has lost its efficiency and the NSGAII algorithm has better efficiency in this regard. Consequently, the epsilon algorithm has considerably better performance in small dimensions, and the NSGAII algorithm is more efficient in larger scales. Performance analyses of two algorithms in large dimensions are presented in this part based on the evaluation of the pareto front in assessing the dimensions of the research problem.

In this part, first, the deterministic model was solved classically, and then the deterministic and stable model was solved using the epsilon limit method. Since robust optimization is one of the approaches that works exceptionally proficiently in circumstances where there is instability, in this inquiry, the instability of the issue has been examined by applying the robust optimization approach. Classical optimization methods ignore data uncertainty and solve the problem as if the nominal data or our guesses are the same as the real data. One of the most important problems of classical optimization models is the assumption of data certainty in optimization problems. However, in a wide range of real-world problems, available data are uncertain and imprecise. To produce its products, Mihan company has five raw material suppliers, three production locations, four distribution centers (warehouses) and five customer markets. The required number of raw materials 1, 2, 3, 4, and 5 are 5, 2, 7, 12, and 6 units, respectively. Final products can be produced in all three production plants and can be transferred to all four distribution centers. In this case study, supply chain planning is done for a period of 5 years. Other required data were explained in the previous sections.

After solving the model, in the first part, Table 7 shows the suppliers that were selected for the raw material. The second part of Table 7 states which distribution centers should keep the product in the warehouse during which periods. It can be seen that only warehouse 1 needs to be open in all five time periods and store the final product, and retaining and using other warehouses is not economically justified. The third part of the Table 7 shows how much the optimal amount of production of each production line of the factory should be in different periods of time. Although the production outputs of factory lines remain numerically consistent across all periods, this pattern reflects the optimization model’s preference for a steady production rate to reduce start-up/shutdown costs, ensure freshness, and stabilize supply to distribution centers. Inventory and supplier selection, however, vary across periods in response to dynamic constraints, illustrating adaptive behavior within a consistent production strategy.

Table 7. Selection of raw material suppliers, operational plan of distribution centers and production lines

	Vital substance 1		Vital substance 2		distribution centers operating plan				optimal production of factory		
Time period	supplier 1	supplier 2	supplier 1	supplier 2	inventory 1	inventory 2	inventory 3	inventory 4	production line 1	production line 2	production line 3
1	-	*	*	*	*	*	*	*	5584	5867	4169
2	*	*	*	*	*	-	-	-	5584	5867	4169
3	-	*	*	*	*	-	-	-	5584	5867	4169
4	-	*	*	-	*	*	-	-	5584	5867	4169
5	-	*	*	*	*	-	-	*	5584	5867	4169
6	-	*	*	*	*	*	*	*	5584	5867	4169
7	*	*	*	*	*	-	-	-	5584	5867	4169
8	-	*	*	*	*	-	-	-	5584	5867	4169
9	-	*	*	-	*	*	-	-	5584	5867	4169

Concurrent with the ideal sum of production line generation within the time horizon of 12 months, additionally the parameter, the sum of generation capacity in completely different periods, is concurrent with the primary portion of Table 8. The optimal production value is given in the second part of Table 8. Also, production line 3, which has the lowest amount of production compared to the other two production lines, has most of the excess production to meet the unmet demand, the values of which are shown in the third part of Table 8. In other words, changing the goal of these values is the same as changing the amount of production.

Table 8 shows the percentage of unmet demand in all markets in all periods assuming the priority of the economic function.

Table 8. Percentage of unmet demand

period	market (customer)				
	1	2	3	4	5
1	3.027	0.027	0.027	1.027	0.027
2	2.027	0.027	0.027	0.027	0.027
3	2.027	1.027	1.027	0.027	0.027
4	3.027	2.027	1.027	0.027	0.027
5	4.027	0.027	0.027	0.027	0.027
6	4.027	1.027	1.027	0.027	1.027
7	4.027	0.027	0.027	0.027	0.027
8	2.027	0.027	0.027	0.027	0.027
9	3.027	0.027	0.027	0.027	0.027
10	3.027	0.027	0.027	0.027	0.027
11	3.027	0.027	0.027	0.027	0.027
12	3.027	1.027	0.027	0.027	1.027

Epsilon constraint strategy was also utilized for the case study based on Table 9. The first problem is selected in the proposed models to provide the answers to the pareto front formed in each model.

Table 9. Lexicography consequences of definite and firm problems

Question	Target Functions	T argetType	First Target Value	2nd Target Value	3rd Target Value
Definitive Question	first target	minimizing	4.541E+09	4.633E+09	4.635E+09
	second target	minimizing	4.145E+09	4.319E+09	4.452E+09
	third target	maximizing	2.502E+05	2.329E+05	2.443E+05
Uncertainty 0.1	first target	minimizing	4.585E+09	4.766E+09	4.766E+09
	secind target	minimizing	4.352E+09	4.795E+09	4.820E+09
	third target	maximizing	2.402E+05	2.429E+05	2.543E+05

The subsequent section delineates the sub-objective function (specifically the second and third objective functions) into five distinct intervals. The findings for breakpoints for the second target function transferred to the constraint (values of epsilons) are presented in Table 10.

Table 10. Epsilon values obtained for classical and firm problems

Problem	Objective function	failiure point					
		1	2	3	4	5	6
classic problem	2	2.142E+09	2.315E+09	1.945E+10	2.146E+09	2.355E+09	2.542E+10
robust uncertainty 0.1	2	2.365E+09	2.655E+09	2.954E+09	3.215E+09	2.841E+09	3.354E+09
classic problem	3	241063	246338	256063	214048	241064	240945

Problem	Objective function	failiure point					
		1	2	3	4	5	6
robust uncertainty 0.1	3	233637	241047	214957	236074	20664	210955

In the last step, the problem is solved by placing the obtained values after applying the epsilon constraint and the obtained values for 5 Pareto fronts, as presented in Table 11.

Table 11. Optimal pareto solutions for the mathematical model of the problem

pareto optimal answer	The classic problem			robust uncertainty 0.1		
	Target one.	Target two.	Target tree.	Target one.	Target two.	Target tree.
1	3.214E+09	4.125E+09	253617	3.654E+09	3.956E+09	214045
2	3.365E+09	3.954E+09	263644	3.766E+09	4.124E+09	223028
3	3.457E+09	4.111E+09	264948	3.954E+09	4.137E+09	214043
4	3.342E+09	4.232E+09	269333	3.855E+09	4.359E+09	234617
5	3.459E+09	4.355E+09	283615	4.124E+09	4.563E+09	214046

5. FURTHER DISCUSSION: The findings of this study highlight the distinct advantages and limitations of the NSGA-II and modified epsilon constraint algorithms in addressing multi-objective optimization challenges within perishable product supply chains. NSGA-II's ability to explore a vast search space efficiently positions it as a superior choice for larger and more complex problem dimensions. It achieves higher computational efficiency and diversity in Pareto-optimal solutions, as evinced by its better performance across all three objective functions and a larger number of Pareto solutions. However, the epsilon constraint algorithm demonstrated exceptional precision and solution quality for smaller-scale problems, showcasing its utility in scenarios where accuracy and tightly clustered solutions are prioritized. The computational trade-offs observed between the two algorithms suggest that problem scale and complexity play pivotal roles in determining the ideal optimization approach.

The case study of Mihan Company underscores the practical implications of using these optimization methods in real-world supply chain settings. By analyzing the raw material suppliers, production allocations, and warehouse operations, the study demonstrates the efficacy of the proposed models in minimizing costs, reducing environmental impact, and ensuring efficient resource utilization. The unmet demand analysis reveals critical insights into how supply chain decisions can address customer market priorities while balancing economic, environmental, and social sustainability metrics. Furthermore, the robust optimization approach used in NSGA-II proved invaluable in handling uncertainties, which are common in supply chains, particularly for perishable products like dairy and pharmaceuticals.

This paper examined two case studies. Initially, twelve scenarios were established for the proposed model in the first phase. Subsequently, five products from the drug case study were evaluated using the epsilon constraint method, recognized as an effective strategy for addressing multi-objective problems through a classical framework. It was found that the epsilon constraint method lacked efficiency when applied to problems with more than seven dimensions. Consequently, the NSGAII algorithm was employed for higher-dimensional cases. The NSGAII algorithm is designed for multi-objective problems and incorporates binary coding for decision variable representation, along with probabilistic cycles for parent selection, facilitating the pursuit of optimal solutions. A comparative analysis was then conducted between the NSGAII and epsilon constraint algorithms.

In the next stage, three dairy products with varying expiration dates were analyzed using both the enhanced epsilon-constraint approach and the classical method. The results demonstrate that the epsilon-constrained reinforcement approach is effective in large-scale problems and leads to greater improvements in the objective function compared to the classical approach. A sensitivity analysis was subsequently conducted on three parameters: demand, cost resilience, and the level of uncertainty. The results indicated that the outcomes of the proposed model were advantageous for both case studies and had a significant impact on the objectives.

A sensitivity analysis of important and key parameters reveals changes in the objective functions of the model. Therefore, considering three crucial parameters – demand, uncertainty level, and robustness cost– the problem was solved under various scenarios, and the results were examined. To analyze sensitivity on the demand parameter, 15 scenarios were designed, incorporating a 25% increase and decrease in demand with five different combinations of uncertainty levels. The results are presented in Table 12 and Figure 5.

Table 12. Parameter sensitivity analysis of demand

Scenario	demand	degree of uncertainty	Percentage change in the first goal	Percentage change in the 2nd goal	Percentage change in the 2nd goal
1	No Change	0.8	0.0046	0.2202	0.22020
2	increase	0.7	0.1754	0.0124	0.0124
3	No Change	0.7	0.0046	0.22020	0.22020
4	increase	0.76	0.1834	0.097643	0.097643
5	No Change	0.9	-0.0125	0.097643	0.097643
6	decrease	0.9	-0.1564	-0.26580	-0.26580
7	decrease	0.8	0.17648	-0.225	-0.225
8	decrease	0.7	0.187412	0.803030	0.803030
9	increase	0.6	0.156941	0.04456	0.04456
10	No Change	1	0.0046	0.22020	0.22020
11	increase	0.9	0.17648	-0.26580	-0.26580
12	decrease	0.6	0.17525	0.41250	0.41250
13	increase	0.7	0.17369	-0.014	-0.014
14	increase	0.9	0.17454	0.1758	0.1758
15	decrease	1	0.0425	0.04576	0.04576

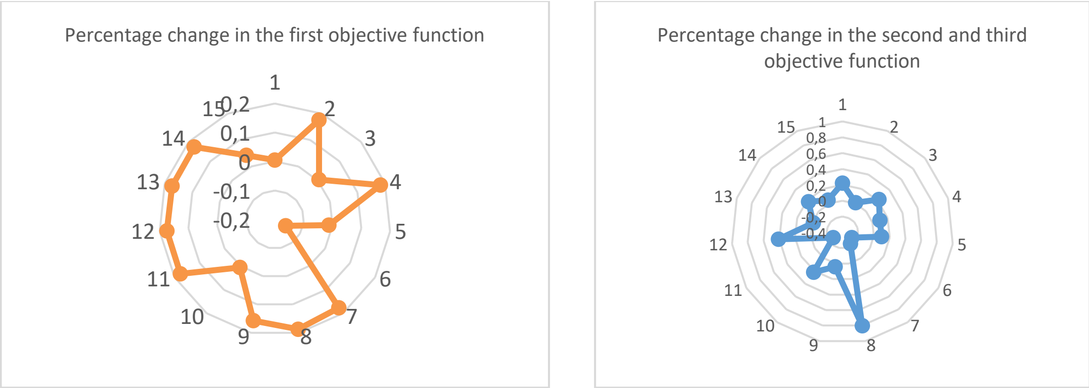

Figure 5. Changes in objective functions relative to different demand parameters

The subsequent phase involved conducting a sensitivity analysis to examine how variations in demand parameters affect the objective functions. Additionally, the analysis focused on the impact of changes in the degree of uncertainty on these objective functions. Figure 6 illustrates that, as the uncertainty degree increases, the objective functions decrease linearly simultaneously. Random probabilities impact the profitability of the company in uncertain scenarios, relative to changes or demand fluctuations.

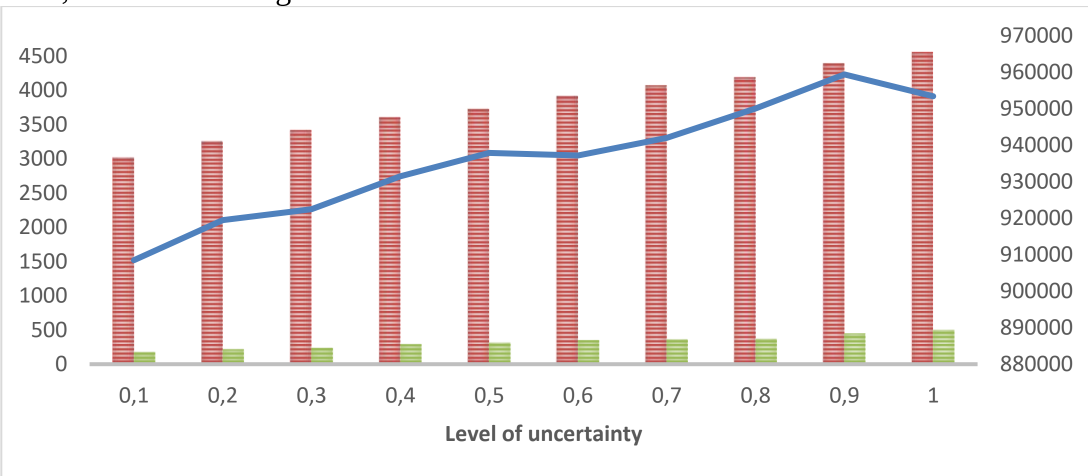

Figure 6. Changes in objective functions relative to different levels of uncertainty

Since the cost of robustification represents the incurred cost to the model after considering uncertainty (discrepancy between deterministic and non-deterministic objective functions), this parameter indicates the amount of error that the model must tolerate in order to approach reality while accounting for uncertainty. To assess the cost of robustification, 5 problems in various dimensions have been designed in an ascending manner, and the values of the first, second, and third objective functions have been calculated in both deterministic and non-deterministic scenarios.

A comparative analysis of recent studies highlights the alignment and advancement of the present model. For instance, Kumar and Agrawal (2024) achieved an 88.4% classification accuracy using CNN for tomato supply chains, significantly enhancing product grading and loss reduction at early supply chain stages. While our model does not utilize image processing, it emphasizes production and routing optimization—achieving over a 25% reduction in expiration-related waste, consistent with the 28.78% food loss reduction reported by Kumar et al. (2025). Furthermore, Huang et al. (2024) showed that REM-supported logistics planning can reduce operation costs by 9%, while our hybrid supply-distribution design achieves similar economic efficiencies through multi-objective integration. Additionally, the proposed formulation supports social dimensions such as job security and accident reduction, contributing a multi-layered sustainability perspective absent in earlier linear or mono-objective models (e.g., Souri & Ghomi, 2025; Komijani & Sajadieh, 2024). This comparison confirms that our work contributes to the literature by offering a more integrated, resilient, and socially sensitive supply chain optimization framework.

The comparative analysis and case study results provide a solid foundation for future research in sustainable supply chain optimization. Leveraging hybrid methodologies that combine the computational speed of NSGA-II with the precision of epsilon constraint methods could offer more balanced and versatile solutions. Additionally, extending the application of these algorithms to other industries with significant perishability challenges, such as fisheries or floral supply chains, could provide valuable insights. Moreover, integrating advanced technologies such as machine learning for dynamic data-driven decision-making and expanding the models to include circular economy principles would further enhance the sustainability and resilience of supply chains. These advancements could address broader global challenges, such as reducing waste, lowering carbon footprints, and ensuring equitable access to essential goods.

6 CONCLUSIONS: The financial difficulties encountered by Iranian enterprises, coupled with associated environmental shortcomings, necessitate a comprehensive consideration of these elements across multiple facets of business design. Historically, the focus has predominantly been on financial and economic aspects; however, in recent decades, the emergence of the concept of sustainability—emphasizing the importance of environmental considerations—has gained prominence in response to escalating environmental challenges, particularly heightened pollution levels. Furthermore, detailed attention to the social aspects that neglecting them at a supply chain level can lead to significant damages throughout the chain, especially in developing countries, adversely affects business partners. The design of supply chain networks has garnered significant interest from scholars in recent times. The uncertainty and presence of ambiguity in the supply chain of these products are considered inseparable. As a result, the sensitivity of work increases in completing this supply chain. Expiration and criticality must always be considered in this process.

In this regard, one of the most important aspects related to expirable goods is the supply chain of expirable items, including food and medicine. The raw materials and products within these two groups are highly susceptible to expiration and have a short lifespan. Also, the production and consumption of such products have significant impacts on the environment and are among the most polluted industries. This study addresses the critical and sensitive nature of supply chain design for perishable goods, specifically within the dairy and pharmaceutical sectors. It proposes a multi-objective mathematical model that encompasses three primary objectives. The first objective is economic in nature, aiming to minimize total costs associated with the supply chain. The second objective seeks to mitigate environmental pollution by analyzing emissions and fuel consumption. The third objective pertains to social sustainability, which is essential for maintaining a resilient supply chain. To effectively integrate sustainability dimensions, social indicators were identified and incorporated into the model through the fuzzy delphi method, drawing on expert insights. The social objective is framed to maximize the function while accounting for uncertainties inherent in the problem and certain model parameters. To address these complexities, a robust optimization strategy, along with an enhanced epsilon-constraint method, has been utilized for solving the multi-objective mathematical models.

The durability of products significantly influences supply chain expenditures, with enhanced product longevity contributing to lower costs within the supply chain. It is recommended that managers prioritize the development of products with extended lifespans, as this approach not only fosters social benefits and mitigates environmental degradation but also promotes economic advancement within the sector. When examining two case studies, it is essential to consider the reliability of the model employed. Nonetheless, the structural characteristics of the supply chains and their associated uncertainty parameters should closely resemble those explored in this study. Consequently, supply chains can adapt their proposed frameworks and methodologies to assess their economic, environmental, and social outcomes. The utilization of robust models, alongside the management of uncertainties in critical parameters, equips managers with the agility needed to navigate unpredictable financial conditions in unfamiliar markets, optimize the flow of materials during production, and sustain demand in a competitive landscape.

The analysis findings indicate that social responsibility in companies is often overlooked. In this study, in addition to proposing an idea for measuring and achieving it within the company, social criteria relevant to companies producing vulnerable products have been evaluated and considered in the modeling. It is advisable for managers and decision-makers to take into account the unpredictable lifespan of perishable goods when designing supply chain networks, particularly for dairy and pharmaceutical items. It is also important to consider environmental risk factors, including fluctuations in exchange rates and inflation, as these can significantly affect supply chain profitability in light of the prevailing economic conditions. Embracing uncertainty can enhance managerial control over long-term production and profitability. Furthermore, it is suggested to explore alternative methods that address uncertainty and to compare their outcomes with the approach proposed in this study. Given the breadth of the concept of sustainability, it is necessary to incorporate sustainability concepts into mathematical modeling for improvement and consideration of all aspects of sustainability. Additionally, other environmental and social impacts, such as employee and supplier training on safety and health issues, accident rates within the company, and non-discriminatory hiring, can be taken into account in decision-making.

Researchers can evaluate the influence of sanctions on decision-making processes and their specific effects on each variable under investigation, taking into account the associated risks. It is advisable for managers and decision-makers to opt for vehicles that produce lower levels of environmental pollution, as the strategic placement of facilities can lead to a notable decrease in environmental impact. Additionally, the costs associated with the supply chain may be diminished through the implementation of recycling initiatives, prompting managers to prioritize these operations in light of elevated production expenses. The primary limitations of this study stem from the absence of a dedicated database for transportation costs, necessitating the reliance on driver assessments for cost estimation, as well as the demand estimation based on expert evaluations from the case study. Moreover, the study faced a lack of timely access to information and significant companies' refusal to provide information about their activities.

6.1. Managerial implementation: The insights derived from this study provide actionable strategies for supply chain managers, particularly in industries dealing with perishable products such as dairy and pharmaceuticals. By leveraging the NSGA-II algorithm, managers can efficiently navigate the complexities of large-scale supply chains, balancing cost efficiency, environmental impact, and service levels. This method offers the flexibility to handle uncertainties in supply chain parameters, allowing for real-time adjustments to production schedules, supplier selection, and inventory management. On the other hand, the modified epsilon constraint algorithm can be applied to smaller-scale problems or segments of the supply chain requiring high precision, such as optimizing warehouse operations or distribution routes. Managers can implement these tools to design robust and sustainable supply chains, reducing waste, improving delivery timelines, and enhancing customer satisfaction. These models also support strategic decision-making by identifying trade-offs between competing objectives, enabling managers to align supply chain performance with organizational sustainability goals.

6.2. Theoretical implications: This study makes a substantial contribution to the theoretical framework of sustainable supply chain optimization by combining robust optimization methods with multi-objective decision-making approaches. It demonstrates the adaptability of the NSGA-II and epsilon constraint algorithms in addressing the unique challenges of perishability, uncertainty, and sustainability in supply chains. The study enriches existing literature by combining economic, environmental, and social dimensions into a unified optimization model, emphasizing the importance of addressing social sustainability metrics often overlooked in supply chain research. Furthermore, it introduces a comparative evaluation of meta-heuristic and constraint-based methods, offering a nuanced understanding of their applicability in various contexts. These theoretical contributions pave the way for future studies to explore hybrid algorithms, integrate advanced data analytics, and extend the principles established in this study to broader supply chain scenarios, thereby advancing both the science and practice of sustainable supply chain management.

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