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Original paper

Designing sustainable supply chains for perishable products under uncertainty: A fuzzy robust multi-objective possibilistic approach

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Abstract

In the context of developing a robust multi-objective optimization framework for designing sustainable supply chain networks for perishable items under uncertainty, this paper provides an overview of a possibilistic framework. Using the three pillars of sustainability (i.e., economic, environmental, and social), the proposed framework seeks to minimize overall supply chain costs, minimize CO_2 emissions, and maximize regional employment opportunities. The proposed framework addresses the uncertainties associated with product demand (sales), shelf life, and shipping/transportation conditions. To accomplish this, the proposed framework employs fuzzy trapezoidal numbers (which can model how much variation a number might have) in combination with a robust possibilistic programming structure. The objective of the proposed framework is twofold: 1) to solve for and balance each of the objectives and 2) to use GAMS to implement the LP-Metric method. Validation of the model has been conducted through extensive utilization of numerical experiments to create a variety of examples (small, medium, and large-sized), which support the proposed approach's ability to produce stable (balanced) solutions, regardless of the size of the example. Additionally, results indicate that the cost of the system (i.e., total supply chain cost) increases with the size of the network, while the number of employment opportunities created is directly related to network size; the amount of environmental impact is not increased by network size. Finally, results from the model establish that the proposed robust possibilistic approach exhibits superior performance to traditional models based solely upon determinism by producing consistently higher levels of reliability and resiliency within supply chain configurations, thereby providing an invaluable source of potential inputs for the management of perishable goods.

Keywords: Sustainable supply chain, perishable products, robust possibilistic programming, fuzzy optimization, multi-objective model, uncertainty.

1 Introduction

Global population growth, along with increases in international trade, has created an increased requirement for supply chain networks that are cost-effective, environmentally sustainable, and socially equitable (which is especially important for perishable products—fresh food/dairy/pharmaceuticals/biologicals—due to the time sensitivity, temperature sensitivity, or quality deterioration associated with those products) and addresses the unique challenges that supply chain

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planning faces as a result of this product type [12, 16]. Inefficient management practices are one of the largest contributors to food waste on a global basis and also represent a large source of greenhouse gas emissions and economic losses. Therefore, the creation of optimization frameworks that address economic, environmental, and social performance indicators simultaneously is critical [11, 19]. Perishable supply chains do not have long enough lead times for sequential decision-making like conventional supply chains, so they require a significantly higher level of coordination in making rapid decisions across multiple echelons under considerable uncertainty. Demand variability, uncertainty regarding the lifespan of the product, and changing transportation conditions (i.e., traffic congestion or delays in deliveries) are the primary uncertainties that impact both the efficiency and sustainability of perishable supply chains [32]. Classical deterministic models do not allow for variations in the real world (sampled populations) and therefore frequently result in infeasible or suboptimal solutions [5, 32]. In an effort to overcome these restrictions, many researchers have turned to advanced modeling techniques that are able to deal with uncertain and unknown data. Examples of these advanced modeling techniques include fuzzy logic, stochastic programming, and possibilistic programming, which are widely used for representing uncertainties in supply chain optimization [10, 15, 22]. Possibilistic programming has a greater ability to model uncertainty as opposed to randomness because it utilizes fuzzy set theory to define unpredictable parameters using possibility distributions instead of probability distributions [4]. This is of particular urgency for perishable supply chains because historical data is often lacking and unreliable, and most parameter estimates will come from expert judgment instead of historical data.

Over time, sustainable supply chain design has changed from being focused solely on minimizing costs to a complete Triple Bottom Line (TBL) approach with regard to economic viability, environmental sustainability, and social responsibility. A mixed-integer nonlinear programming model was developed by Al-Ashhab et al. [1] for sustainability-oriented supply chains that deal with perishable goods using both profit maximization and the reduction of environmental impact as objectives. The researchers demonstrated that sustainability-focused supply chain models can significantly lower waste due to spoilage without affecting profits. Lahri et al. [14] introduced a two-stage multi-objective possibilistic programming model for designing environmentally friendly and socially responsible supply chain networks. This model allowed for the simultaneous optimization of cost, emissions, and employment while accounting for epistemic uncertainty. Hybrid robust possibilistic programming models have further progressed the discipline by providing increased flexibility in the solutions developed. Baghizadeh et al. [2] created a hybrid robust possibilistic model of sustainable agricultural supply chains that considered uncertainty related to economic factors, social impacts, and environmental aspects by using fuzzy sets and implemented a queuing system to schedule transportation. Ghaderi et al. [8] were successful in demonstrating that modestly increasing costs (i.e., 2–3%) would produce large benefits for both the environment and social equity using robust possibilistic programming in bioethanol supply chain design. Savoji et al. [24] built upon this methodology in green biofuels by simultaneously reducing cost and CO_2 emissions under conditions of anticipated demand uncertainty.

Perishable supply chains involve complexities due to uncertainty, including demand variability and product expiry dates, which makes them especially challenging to manage. In this context, Tehrani and Gupta [29] investigated how to integrate different types of uncertainties – namely probabilistic and fuzzy – into sustainable closed-loop tire supply chains using probabilistic demand modeling and fuzzy methods for production and return uncertainty. Soon et al. [27] also validated the use of possibilistic programming in designing closed-loop networks for multiple quality goods and demonstrated that they provided stable solutions regardless of the degree of uncertainty experienced. While these studies contain significant findings, there are still significant research gaps in this field. Most prior research only considers one or two of the three dimensions of sustainability; in other words, none have integrated all three pillars of TBL in an optimization framework specifically designed for perishable goods. Additionally, most of the previous research treats each source of uncertainty in isolation - either demand-related or capacity-related – rather than considering the simultaneous impact that each source would have when viewed together on supply chain performance. Finally, there has yet to be any thorough quantitative analysis of deterministic and robust probabilistic models that would allow decision-makers to evaluate trade-offs among cost, emissions, and solution stability.

This paper discusses the development of a fuzzy robust possibilistic multi-objective optimization model to fill gaps in the design of a sustainable perishable food supply chain (PFSC) network. The model combines the three supply chain levels of manufacture, distribution and retail into a unified optimization framework. It pursues three objectives simultaneously: 1) minimize the total supply chain costs (i.e., fixed facility-opening costs, production costs, inventory holding costs, transportation costs, and fuel costs) 2) minimize the CO_2 emissions produced throughout the supply chain (i.e., facility operations, production, storage, and transportation) 3) create as many jobs as possible in the manufacture and distribution centers (the social dimension of sustainability). As part of the model's development, three critical uncertain parameters (customer demand, uncertainty associated with the length of the product shelf life, and uncertainty associated with traffic conditions) are represented using trapezoidal fuzzy numbers to reflect the inherent imprecision involved. These fuzzy numbers are then processed using a robust possibilistic programming framework to convert the fuzzy multi-objective model into an equivalent deterministic model, thereby ensuring solution feasibility and stability for a range of uncertainty outcomes. The resulting multi-objective problem will be solved using the LP-metric method implemented in GAMS. The LP-metric scalarizes the three objectives into one composite metric by determining the normalized distances from the ideal values for each of the three objectives.

This research makes three important contributions. The first contribution is that the study provides a complete integration of TBL into the perishable product supply chain. The previous literature that has addressed sustainability dimensions has done so either partially, separately, or not at all. The TBL model presented in this research simultaneously integrates cost, CO_2 emissions, and workforce into a single system designed specifically for distribution of perishable food products that have limitations on shelf life. The second contribution is that the research develops an approach to integrated uncertainty modelling using a multi-source integrated uncertainty modelling approach. The TBL model combines three separate sources of uncertainty, which are represented through trapezoidal fuzzy parameters used within a robust possibilistic programming framework. The TBL model treats uncertainty as a system characteristic rather than separate characteristics, capturing the combined influence of demand uncertainty, variability of shelf life, and the unpredictability of traffic conditions. Lastly, the TBL model provides a practical method of integrating practical applications into research methodologies. By combining robust possibilistic programming and the LP-metric solution technique with the General Algebraic Modeling System (GAMS), the model has created an efficient and effective decision-support tool for the distribution of perishable food products. A systematic comparison of deterministic and robust solutions has produced trade-off measurements between cost efficiency, environmental performance, and solution stability; therefore, generating practical information that supply chain decision makers can utilize.

2 Research background

This research aims to provide a clearer understanding of where the current study fits in the existing body of knowledge on sustainable supply chain modeling, with an emphasis on handling uncertainty. Table 1 shows how various studies relate to each other through a systematic comparison of key features that characterize the original studies, rather than a summary format (i.e., paragraphs). The comparison is displayed in a table format using a feature basis (i.e., ✓ or -) and allows the reader to quickly determine which features have been addressed by previous studies versus those where no such feature has been identified in previous literature. The criteria used to compare different studies include: 1. Consideration of products with a limited useful life. 2. Multi-objective formulation. 3. Inclusion of social sustainability Consequently, little research has focused on simultaneously minimizing costs and CO2 emissions while maximizing job creation in highly perishable food supply chains." Why it works: It replaces the vague "optimizing for" with precise mathematical/operational verbs ("minimizing" costs/emissions and "maximizing" job creation). It also changes "extremely" to the more standard academic term "highly." as an objective. 4. Use of fuzzy variables. 5. Possibilistic programming. 6. Robust optimization method of solution development. 7. Integrated model that considers multiple sources of uncertainty (i.e., simultaneous consideration of demand, shelf-life, traffic/logistics uncertainties). 8. Multi-echelon network configuration. 9. Method of creating a solution. Table 1 systematically analyzes three major gaps in research, which inspire the current study. Specifically, there is an incomplete incorporation of the triple bottom line in optimization models used to describe the production and distribution of very perishable items. Although a number of studies have proposed multi -objective formulations [25, 30, 31], only a small number include all three types of sustainability (economic, environmental, and social) as a part of a holistic optimization approach for highly perishable food supply chains. As shown in Table 1, studies that incorporate social objectives such as job creation and equitable distribution, rarely focus on highly perishable foods. Conversely, many studies models overlook social impacts. Consequently, little research has focused on simultaneously minimizing costs and, CO_2 emission while maximizing job creation in highly perishable food supply chains. Second, the literature demonstrates an inconsistency in the treatment of multiple sources of uncertainty. Most current models account for only a single source of uncertainty, typically focusing on either demand variability [7, 31] or capacity uncertainty [29]. In fact, most perishable supply chains are impacted by a number of interrelated sources of uncertainty, which occur at the same time, including customer demand changes, product shelf life variations and transportation conditions (such as traffic congestion) that are subject to change. As shown in the multi-source uncertainty column of Table 1, no study to date has considered the combined effects of these three sources of uncertainty in a comprehensive robust possibilistic framework. The fragmented approach reduces the practical use of the current models since they do not adequately represent the systemic character of uncertainty as it exists in perishable supply chains in real life third, there has been no systematic comparison of different modeling approaches such as deterministic versus robust. Although there is also an increase in the number of usage of both robust and possibilistic methods, the currently available research offers only a limited amount of rigorous, quantitative, and systematic comparison between deterministic solution and robust possibilistic solution. Addressing this gap is critical,

Table 1: Comparative analysis of related studies on sustainable supply chain optimization under uncertainty

Author(s)	**Perishable**	**Multi-Objective**	**Social Objective**	**Fuzzy Parameters**	**Possibilistic Programming**	**Robust Approach**	**Integrated Uncertainty (Demand + Shelf Life + Traffic)**	**Multi-Echelon Network**	**Solution Method**
Ren et al. [23]	✓	–	–	–	–	–	–	–	Analytical
Bairamzadeh et al. [3]	–	✓	✓	–	✓	✓	–	✓	CPLEX
Tsao et al. [31]	–	✓	✓	✓	–	–	–	✓	Fuzzy MOP
Moghaddam et al. [28]	✓	✓	✓	–	–	–	–	–	Reverse Logistics
Mohammed et al. [18]	–	✓	✓	✓	–	–	–	–	MCDM-FMOO
Dutta & Shrivastava [7]	✓	–	–	–	–	–	–	✓	Stochastic Prog.
Tehrani & Gupta [29]	–	✓	–	✓	✓	–	–	✓	ε-constraint
Wang et al. [34]	–	✓	–	–	–	–	–	✓	MIP
Tirkolaee & Aydin [30]	✓	✓	✓	✓	✓	–	–	✓	Bi-Level PLP
Soon et al. [27]	–	✓	✓	–	✓	✓	–	✓	RPP
Daryanian et al. [6]	✓	✓	✓	✓	–	✓	–	✓	Fuzzy Robust
Gitinavard et al. [9]	✓	✓	–	✓	✓	–	–	✓	Bi-Stage PP
Shakuri & Barzinpour [25]	✓	✓	✓	–	–	–	–	✓	CVaR + Stochastic
Ubud & Putra [33]	✓	–	–	–	–	–	–	–	Integrated Model
Present Study	✓	✓	✓	✓	✓	✓	✓	✓	**LP-Metric / GAMS**

as decision-makers would benefit from understanding the trade-offs in cost-effectiveness, environmental performance, and solution stability across different modeling approaches. This issue is of even greater importance in the management of perishable supply chains than in other supply chain contexts. If an accepted model becomes infeasible to execute, the consequences can be severe and irreversible, e.g., spoiled or stock-outs.

This research addresses all three gaps by creating a fuzzy robust possibility multi-objective optimization model that optimizes costs, CO_2 emissions, and job creation across the entire three echelon perishable food supply chain from manufacturing centers to distribution centres to retailers; incorporates uncertainty about demand, variability of shelf life, and variability in traffic conditions (that is, onto a trapezoidal fuzzy variable) into the design of the supply chain using a robust possibility programme; and provides a systematic comparison between deterministic and robust solutions in order to quantify trade-offs between economic efficiency, environmental impact and decision robustness. This research has both theoretical and practical contributions. Theoretically, it expands the application of robust possibility programming into the low carbon logistics for perishable food—specifically, incorporating social sustainability (i.e., job creation) into the decision making process along with economic and environmental metrics as an optimization criterion. Practically, it has developed a reliable, flexible and computationally low cost optimization tool for supply chain logistics decision-makers to create low carbon and socially responsible supply chains. The optimization tool can be implemented in GAMS, using LP-metric method, in order to design a resilient supply chain network that is also financially and environmentally sound.

3 Proposed model

The study examines the perishable food supply chain by proposing flexible strategies to address uncertainties arising from traffic variability and limited product shelf life. It develops a theoretical network consisting of production centers (PCs), distribution centers (DCs), and retailers, modeling product flows from PCs to DCs and then to retailers through multiple routes that may be disrupted by traffic or environmental conditions. The delivery process emphasizes optimal vehicle sizing to maximize load efficiency while ensuring that orders are delivered within the product shelf-life constraint $(t+LF_p)$. A multi-objective optimization model is introduced to minimize total costs and environmental impacts while improving supply chain efficiency and sustainability. The research first formulates a deterministic network optimization model, which is then extended into a robust possibilistic programming framework incorporating fuzzy uncertainties to capture economic, environmental, and social dimensions. The deterministic and robust models are compared against a baseline scenario to assess their relative robustness and overall performance. Finally, a case study validates the applicability and effectiveness of the proposed approach, supported by detailed analysis of indices, parameters, and decision variables, demonstrating the model's capability to support innovative, sustainable, and risk-aware decision-making in perishable food supply chains. To thoroughly evaluate the applicability and performance of the proposed robust possibilistic multi-objective model, a comprehensive dataset was generated. Given the inherent difficulties in acquiring a complete, real-world database that encompasses all economic, environmental, and social parameters under uncertainty, the required data were systematically simulated and adapted from representative values in the recent perishable food supply chain literature. Specifically, the baseline deterministic values for transportation costs, facility establishment costs, required labor hours, and CO_2 emission factors were extracted and calibrated from well-established studies, including Ghaderi et al. [8], Baghizadeh et al. [2], and Savoji et al. [24]. These parameters were carefully adjusted to reflect realistic operational conditions and constraints typical of modern perishable food distribution networks, which consist of Production Centers (PCs), Distribution Centers (DCs), and Retailers connected via multiple transport routes. To capture the highly volatile nature of perishable logistics, key uncertain parameters—namely product demand, limited shelf life, and traffic variability—were modeled using trapezoidal fuzzy numbers, denoted as $\tilde{v} = (v_1, v_2, v_3, v_4)$. The precise formulation of these fuzzy numbers (i.e., their optimistic, pessimistic, and most likely values) was constructed by combining the historical variation ranges reported in the aforementioned literature with expert judgments from supply chain practitioners. This approach ensures that the simulated uncertainty effectively mimics real-world disruptions. Furthermore, to test the model's computational tractability and scalability, the generated database was categorized into small-, medium-, and large-scale test instances. Each instance progressively increases the number of network nodes (PCs, DCs, and Retailers) and available routing options. This structured dataset enables a rigorous assessment of how the proposed robust possibilistic framework behaves in terms of execution time, total cost, emissions, and job creation as the complexity of the supply chain expands.

Index Sets

- $N = \{1, \dots, n\}$: Set of available transportation routes.
- $R = \{1, \dots, r\}$: Set of retailers.
- $P = \{1, \dots, p\}$: Set of products.
- $T = \{1, \dots, t\}$: Set of planning periods.
- $V = \{1, \dots, v\}$: Set of vehicle types.
- $D = \{1, \dots, d\}$: Set of distribution centers.
- $M = \{1, \dots, m\}$: Set of manufacturing centers.

Parameters

- FC_{mt}: Fixed cost of opening manufacturing center m in period t.
- FC_{dt}: Fixed cost of opening distribution center d in period t.
- FC_{dmt}: Fixed assignment cost of distribution center d to manufacturing center m in period t.
- FC_{ndt}: Fixed assignment cost of retailer r to distribution center d in period t.
- SC_{mdvt}: Transportation cost of product p from manufacturing center m to distribution center d using vehicle v in period t.

- SC_{drvt}: Transportation cost of product p from distribution center d to retailer r using vehicle v in period t.
- CHl_{dt}: Inventory holding cost in distribution center d in period t.
- PC_{pmt}: Production cost of product p in manufacturing center m during period t.
- CF_{vt}: Fuel cost of vehicle v considering traffic conditions in period t.
- RE_{mt}: CO_2 emission due to opening manufacturing center m.
- RE_{dt}: CO_2 emission due to opening distribution center d.
- RE_{pdt}: CO_2 emission from storing product p in distribution center d.
- RE_{pmdvt}: CO_2 emission from transporting product p from manufacturing center m to distribution center d using vehicle v.
- RE_{pdrvt}: CO_2 emission from transporting product p from distribution center d to retailer r using vehicle v.
- RE_{vrt}: CO_2 emission from restarting vehicle v at retailer r.
- RE_{pmt}: CO_2 emission generated during the production of product p in manufacturing center m.
- MD_{prt}: Maximum demand of retailer r for product p in period t.
- MS_{drvt}: Maximum allowable service time considering traffic conditions for delivery from d to r using vehicle v.
- DS_{dr}: Distance between distribution center d and retailer r.
- C_v: Capacity of vehicle v.
- CD_d: Capacity of distribution center d.
- CP_m: Capacity of manufacturing center m.
- PE_{rpt}: Price elasticity of demand for product p at retailer r in period t.
- STL_{rvt}: Late service time for retailer r by vehicle v in period t.
- STE_{rvt}: Early service time for retailer r by vehicle v in period t.
- LST_{rvt}: Latest allowable service time.
- EST_{rvt}: Earliest allowable service time.
- RCF_{drvt}: Fuel consumption rate of vehicle v when delivering from distribution center d to retailer r under traffic conditions in period t.
- RVN_{ndt}: Equals 1 if route n in period t goes to distribution center d; 0 otherwise.
- RVR_{nrt}: Equals 1 if route n in period t goes to retailer r; 0 otherwise.
- LF_p: Shelf life of product p.
- SD_{dt}: Number of job opportunities created in distribution center d in period t.
- SP_{mt}: Number of job opportunities created in manufacturing center m in period t.
- SD_{Max}: Maximum allowable job opportunities in distribution centers.
- SP_{Max}: Maximum allowable job opportunities in manufacturing centers.
- M: Big number.

Decision Variables

- SL_{rvt}: Service level provided to retailer r by vehicle v in period t.

- AT_{rvt}: Arrival time of vehicle v at retailer r in period t.
- DT_{rvt}: Departure time of vehicle v from retailer r in period t.
- AD_{rpt}: Actual demand of retailer r for product p in period t.
- XPd_{pmdvt}: Quantity of product p transported from manufacturing center m to distribution center d using vehicle v in period t.
- Xr_{pdrvt}: Quantity of product p transported from distribution center d to retailer r using vehicle v in period t.
- Xp_{pmt}: Quantity of product p produced in manufacturing center m in period t.
- Ip_{dt}: Inventory level of product p in distribution center d in period t.
- IL_{prt}: Inventory level of product p in retailer r in period t.
- SP_{prt}: Maximum selling price of product p at retailer r.
- USP_{prt}: Actual selling price of product p at retailer r.
- OD_{dt}: 1 if distribution center d is open in period t; 0 otherwise.
- OP_{mt}: 1 if manufacturing center m is open in period t; 0 otherwise.
- γ_{rdt}: 1 if retailer r is assigned to distribution center d in period t; 0 otherwise.
- δ_{dmt}: 1 if distribution center d is assigned to manufacturing center m in period t; 0 otherwise.
- μ_{vnt}: 1 if vehicle v is selected for route n in period t; 0 otherwise.
- Y_{nrvt}: 1 if route n using vehicle v delivers to retailer r in period t; 0 otherwise.
- Z_{nt}: 1 if route n is used in period t; 0 otherwise.

3.1 Mathematical model

The document presents a comprehensive mathematical model for supply chain optimization based on three objective functions: (1) minimizing total supply chain costs, including fixed equipment, allocation, production, inventory holding, transportation, fuel consumption, and traffic-dependent costs; (2) minimizing total CO_2 emissions from transportation, storage, and production activities; and (3) maximizing job creation across the supply network, subject to employment capacity limits at production and distribution centers to support social sustainability. The model incorporates detailed constraints to ensure feasibility and consistency. Constraints (6)–(8) enforce balanced material flows at all facilities. Constraints (9) and (10) limit storage capacity at distribution centers and production capacity at manufacturers, while constraints (11)–(13) prevent overproduction and the storage of perishable products beyond their expiration dates. Constraints (14) and (15) impose vehicle capacity limits, and constraints (16) and (17) prevent overlapping or ambiguous assignments. Constraints (18)–(20) restrict allocations to open facilities only, and constraints (21) and (22) ensure that each retailer is assigned to exactly one distribution center or producer. Furthermore, constraints (23) and (24) capture pricing dynamics influenced by product shelf life and retailer demand. Constraints (25)–(32) address transportation scheduling by considering travel start times, vehicle capacities, travel durations, and traffic conditions to determine service levels and ensure timely deliveries. Overall, the model integrates economic, environmental, and social objectives while enhancing operational reliability and minimizing logistical violations across the supply chain.

$$\begin{aligned}\text{Min } Z_1 = &\sum_{m=1}^{M}\sum_{t=1}^{T} FC_{mt}.OP_{mt} + \sum_{d=1}^{D}\sum_{t=1}^{T} FC_{dt}.OD_{dt} + \sum_{d=1}^{D}\sum_{m=1}^{M}\sum_{t=1}^{T} FC_{dmt}.\delta_{dmt}\\ &+ \sum_{r=1}^{R}\sum_{d=1}^{D}\sum_{t=1}^{T} FC_{rdt}.\gamma_{rdt} + \sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{t=1}^{T} PC_{pmt}.Xp_{pmt}\\ &+ \sum_{p=1}^{P}\sum_{d=1}^{D}\sum_{t=1}^{T} CHI_{dt}.I_{pdt} + \sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{d=1}^{D}\sum_{v=1}^{V}\sum_{n=1}^{N}\sum_{t=1}^{T} SC_{dmt}.Xpd_{pmdvt}\\ &+ \sum_{p=1}^{P}\sum_{d=1}^{D}\sum_{r=1}^{R}\sum_{v=1}^{V}\sum_{n=1}^{N}\sum_{t=1}^{T} SC_{drvt}.Xdr_{pdrvt} + \sum_{d=1}^{D}\sum_{r=1}^{R}\sum_{n=1}^{r\cup d}\sum_{v=1}^{V}\sum_{t=1}^{T} SC_{mdvt}.Xpd_{pmdvt},\end{aligned} \tag{1}$$

$$\begin{aligned}\text{Min } Z_2 = &\sum_{p=1}^{p}\sum_{m=1}^{M}\sum_{d=1}^{D}\sum_{r=1}^{R}\sum_{v=1}^{V}\sum_{t=1}^{T} Ds_{dr}.Ms_{drvt}.(RE_{drt} + Xpd_{pdrvt}.RE_{pmdvt})\\ &+ \sum_{p=1}^{p}\sum_{d=1}^{D}\sum_{t=1}^{T} RE_{pdt}.I_{pdt} + \sum_{m=1}^{M}\sum_{t=1}^{T} RE_{mt}.OP_{mt} + \sum_{d=1}^{D}\sum_{t=1}^{T} RE_{dt}.OD_{dt}\\ &+ \sum_{p=1}^{p}\sum_{m=1}^{M}\sum_{t=1}^{T} RE_{pmt}.XP_{pmt}\end{aligned} \tag{2}$$

$$\text{Max } Z_3 = \sum_{d=1}^{D}\sum_{t=1}^{T} SD_{dt}.OD_{dt} + \sum_{d=1}^{D}\sum_{t=1}^{T} SP_{mt}.OP_{mt}. \tag{3}$$

$$SD_{dt}.OD_{dt} \le SD_Max \qquad \forall d,t. \tag{4}$$

$$SP_{dt}.OP_{dt} \le SP_Max \qquad \forall d,t. \tag{5}$$

$$Xp_{pmt} = \sum_{d=1}^{D}\sum_{v=1}^{V} Xpd_{pmdvt} \qquad \forall m,p,t. \tag{6}$$

$$I_{pd(t-1)} + \sum_{m=1}^{M}\sum_{v=1}^{V} Xpd_{pmdvt} = \sum_{v=1}^{V}\sum_{r=1}^{R} Xdr_{pdrvt} + I_{pdt} \qquad \forall p,d,t. \tag{7}$$

$$\sum_{d=1}^{D}\sum_{v=1}^{v} Xdr_{pdrvt} + IL_{pdt(t-1)} = AD_{prt} + IL_{prt} \qquad \forall p,r,t. \tag{8}$$

$$\sum_{p=1}^{P} I_{pdt} \le CD_d.OD_{dt} \qquad \forall d,t. \tag{9}$$

$$\sum_{p=1}^{P} Xp_{pmt} \le CP_m.OP_{mt} \qquad \forall m,t. \tag{10}$$

$$I_{pd(t-1)} \le \sum_{r=1}^{r}\sum_{t'\ge t}^{t'\le(t+LF_p)} AD_{prt'}.Y_{rdt'} \qquad \forall p,d,t. \tag{11}$$

$$IL_{pr(t-1)} \le \sum_{t'\ge t}^{t'\le(t+LF_p)} AD_{prt'} \qquad \forall p,t. \tag{12}$$

$$\sum_{m=1}^{M} Xp_{pm(t-1)} \le \sum_{t'\ge t}^{t'\le(t+LF_p)} AD_{prt'} \qquad \forall p,t. \tag{13}$$

$$\sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{d=1}^{D} Xpd_{pmdvt\leq} C_v.\mu_{vnt} \qquad \forall v,n,t. \tag{14}$$

$$\sum_{p=1}^{P}\sum_{d=1}^{D}\sum_{r=1}^{R} Xdr_{pdrvt\leq} C_v.\mu_{vnt} \qquad \forall v,n,t. \tag{15}$$

$$\sum_{p=1}^{P}\sum_{v=1}^{V} Xdr_{pdrvt\leq} M.\gamma_{rdt}.\mu_{vnt} \qquad \forall r,d,t. \tag{16}$$

$$\sum_{p=1}^{P}\sum_{v=1}^{V} Xpd_{pmdvt\leq} M.\delta_{dmt} \qquad \forall m,d,t. \tag{17}$$

$$\gamma_{rdt} \leq OD_{dt} \qquad \forall r,d,t. \tag{18}$$

$$\delta_{dmt} \leq OD_{dt} \qquad \forall d,m,t. \tag{19}$$

$$\delta_{dmt} \leq OP_{mt} \qquad \forall d,m,t. \tag{20}$$

$$\sum_{d=1}^{D} \gamma_{rdt\leq} 1 \qquad \forall t,r. \tag{21}$$

$$\sum_{m=1}^{M} \delta_{dmt\leq} 1 \qquad \forall t,d. \tag{22}$$

$$AD_{prt} = MD_{prt-PE_{prt}} \qquad \forall p,r,t. \tag{23}$$

$$USP_{prt} = \Big(USP_{pr(t-1)} - \frac{SP_{prt}}{LF_p}\Big).\Big(1-\sum_{d=1}^{D}\gamma_{rdt}) + SP_{prt}.(\sum_{d=1}^{D}\gamma_{rdt}\Big) \qquad \forall p,r,t. \tag{24}$$

$$SL_{rvt} \leq \frac{1+0.15.(\frac{DT_{vrt}-AT_{vrt}}{C_v})^4 - STL_{rvt}}{LST_{rvt}-STL_{rvt}} \qquad \forall r,v,t. \tag{25}$$

$$SL_{rvt} \leq \frac{STE_{rvt}-1+0.15.(\frac{DT_{vrt}-AT_{vrt}}{C_v})^4 - STL_{rvt}}{STE_{rvt}-EST_{rvt}} \qquad \forall r,v,t. \tag{26}$$

$$\sum_{n=1}^{r\cup d} Z_{nt}.RVR_{nrt} \leq 1 \qquad \forall r,t. \tag{27}$$

$$Z_{nt} \leq \sum_{d=1}^{D} RVR_{nrt}.OD_d \qquad \forall n,t. \tag{28}$$

$$DT_{vrt} \leq AT_{vrt} + \sum_{d=1}^{D}\frac{DS_{dr}}{MS_{drvt}}.(1+0.15(\frac{DT_{vrt}-AT_{vrt}}{C_v})^4) + M.(1-Y_{nvrt}) \quad \forall v,r,t,n. \tag{29}$$

$$DT_{vrt} \leq AT_{vrt} + \sum_{d=1}^{D}\frac{DS_{dr}}{MS_{drvt}}.(1+0.15(\frac{DT_{vrt}-AT_{vrt}}{C_v})^4) + M.(1-Y_{nvrt}) \quad \forall v,r,t. \tag{30}$$

$$AT_{vrt} \geq STL_{rvt} \qquad \forall v,r,t. \tag{31}$$

$$DT_{vrt} \geq STE_{rvt} \qquad \forall v,r,t. \tag{32}$$

$$\sum_{n=1}^{N} \mu_{vnt} \leq M.Z_{nt} \qquad \forall n,t. \tag{33}$$

$$\sum_{r=1}^{R} Y_{nvrt} \leq M.\mu_{vnt} \qquad \forall \nu,n,t. \tag{34}$$

In supply chain management, uncertainty in demand, especially during crises, significantly impacts decision-making and inventory management. This study presents a robust possibility programming approach to model such uncertainty, utilizing trapezoidal fuzzy numbers to represent demand. A new parameter, MDprt (demand uncertainty parameter), will convert fuzzy demand into deterministic values, allowing decision-makers to factor in their uncertainty level and risk tolerance. The robust possibilistic programming method is designed to generate optimal solutions by transforming fuzzy demand into a structured model, which will be elaborated upon in the subsequent sections of the document.

$$\begin{aligned} \text{Min}E(Z_i) =&E(c)x + E(\tilde{B})y, \\ &Nec(\tilde{A}_1 x \leq B_1) \geq a_1, \\ &Nec(\tilde{A}_2 x \leq \tilde{B}_2) \geq a_2, \\ &Nec(\tilde{A}_3 x + R_1 y \leq \tilde{B}_3) \geq a_3, \\ &Nec(\tilde{R}_2 y \leq \tilde{B}_4) \geq a_4, \\ &y \in \{0,1\}, \qquad x \geq 0. \end{aligned} \tag{35}$$

According to the above relationship, a robust probabilistic programming base model is developed for the proposed model. Since constraint (23) involves uncertainty, this constraint must be transformed into two equivalent deterministic constraints based on the probabilistic approach. The transformation form of this probabilistic constraint is given below.

$$\begin{aligned} Min\ Z_1 = &\sum_{m=1}^{M}\sum_{t=1}^{T} FC_{mt}.OP_{mt} + \sum_{d=1}^{D}\sum_{t=1}^{T} FC_{dt}.OD_{dt} + \sum_{d=1}^{D}\sum_{m=1}^{M}\sum_{t=1}^{T} FC_{dmt}.\delta_{dmt} + \sum_{r=1}^{R}\sum_{d=1}^{D}\sum_{t=1}^{T} FC_{rdt}.\gamma_{rdt} \\ &+ \sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{t=1}^{T} PC_{pmt}.Xp_{pmt} + \sum_{p=1}^{P}\sum_{d=1}^{D}\sum_{t=1}^{T} CHI_{dt}.I_{pdt} + \sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{d=1}^{D}\sum_{v=1}^{V}\sum_{n=1}^{N}\sum_{t=1}^{T} SC_{dmt}.Xpd_{pmdvt} \\ &+ \sum_{p=1}^{P}\sum_{d=1}^{D}\sum_{r=1}^{R}\sum_{v=1}^{V}\sum_{n=1}^{N}\sum_{t=1}^{T} SC_{drvt}.Xdr_{pdrvt} + \sum_{d=1}^{D}\sum_{r=1}^{R}\sum_{n=1}^{r\cup d}\sum_{v=1}^{V}\sum_{t=1}^{T} SC_{mdvt}.Xpd_{pmdvt}. \end{aligned} \tag{36}$$

$$AD_{prt} \geq \frac{a_1}{2}.MD_{prt(2)} + \left(1 - \frac{a_1}{2}\right).MD_{prt(1)} - PE_{prt}.USP_{prt}. \tag{37}$$

$$AD_{prt} \leq \frac{a_1}{2}.MD_{prt(3)} + \left(1 - \frac{a_1}{2}\right).MD_{prt(4)} - PE_{prt}.USP_{prt}. \tag{38}$$

In the proposed mathematical model, the parameter MD_{prt} is defined as a trapezoidal fuzzy number, represented by four components: (MD_{prt} (1), MD_{prt} (2), MD_{prt} (3), MD_{prt} (4)). In line with the standard structure of robust possibilistic programming models, the expressions for the expected value E(Z) as well as the bounds Z_{max} and Z_{min} are reformulated into deterministic forms. During this transformation, the coefficients β and β' are introduced as cost factors that reflect the influence of uncertainty within the model. These values also act as penalty parameters in constraints involving uncertainty and are implemented based on the Pishvaee's Possibilistic Robust Programming Approach [20, 21]. This approach allows the model to adapt to the decision-maker's risk aversion or conservatism, thereby producing robust and reliable solutions that can effectively account for the inherent uncertainty in demand.

$$\begin{aligned} Min\ Z = E(Z) + \gamma(Z_{max} - Z_{min}) + \beta.\left[MD_{prt(2)} - (1 - \frac{a_1}{2})MD_{prt(1)} - \frac{a_1}{2}MD_{prt(2)}\right] \\ + \beta^1.\left[\frac{a_1}{2}MD_{prt(3)} + (1 - \frac{a_1}{2})MD_{prt(4)} - MD_{prt(3)}\right]. \end{aligned} \tag{39}$$

$$
\begin{aligned}
E(z) = & \sum_{m=1}^{M}\sum_{t=1}^{T} FC_{mt}.OP_{mt} + \sum_{d=1}^{D}\sum_{t=1}^{T} FC_{dt}.OD_{dt} + \sum_{d=1}^{D}\sum_{m=1}^{M}\sum_{t=1}^{T} FC_{dmt}.\delta_{dmt} + \sum_{r=1}^{R}\sum_{d=1}^{D}\sum_{t=1}^{T} FC_{rdt}.\gamma_{rdt} \\
& + \sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{t=1}^{T} PC_{pmt}.Xp_{pmt} + \sum_{p=1}^{P}\sum_{d=1}^{D}\sum_{t=1}^{T} CHI_{dt}.I_{pdt} + \sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{d=1}^{D}\sum_{v=1}^{V}\sum_{n=1}^{N}\sum_{t=1}^{T} SC_{dmt}.Xpd_{pmdvt} \\
& + \sum_{p=1}^{P}\sum_{d=1}^{D}\sum_{r=1}^{R}\sum_{v=1}^{V}\sum_{n=1}^{N}\sum_{t=1}^{T} SC_{drvt}.Xdr_{pdrvt} + \sum_{d=1}^{D}\sum_{r=1}^{R}\sum_{n=1}^{r\cup d}\sum_{v=1}^{V}\sum_{t=1}^{T} SC_{mdvt}.Xpd_{pmdvt} \\
& - \Big(\frac{MD_{prt(1)} + MD_{prt(2)} + MD_{prt(3)} + MD_{prt(4)}}{4} - PE_{prt}.USP_{prt} - AD_{prt}\Big).\beta' \\
& + \Big(MD_{prt} - \frac{MD_{prt(1)} + MD_{prt(2)} + MD_{prt(3)} + MD_{prt(4)}}{4} + PE_{prt}.USP_{prt}\Big).\beta.
\end{aligned} \tag{40}
$$

$$
\begin{aligned}
\text{Min } Z = & \sum_{m=1}^{M}\sum_{t=1}^{T} FC_{mt}.OP_{mt} + \sum_{d=1}^{D}\sum_{t=1}^{T} FC_{dt}.OD_{dt} + \sum_{d=1}^{D}\sum_{m=1}^{M}\sum_{t=1}^{T} FC_{dmt}.\delta_{dmt} + \sum_{r=1}^{R}\sum_{d=1}^{D}\sum_{t=1}^{T} FC_{rdt}.\gamma_{rdt} \\
& + \sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{t=1}^{T} PC_{pmt}.Xp_{pmt} + \sum_{p=1}^{P}\sum_{d=1}^{D}\sum_{t=1}^{T} CHI_{dt}.I_{pdt} + \sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{d=1}^{D}\sum_{v=1}^{V}\sum_{n=1}^{N}\sum_{t=1}^{T} SC_{dmt}.Xpd_{pmdvt} \\
& + \sum_{p=1}^{P}\sum_{d=1}^{D}\sum_{r=1}^{R}\sum_{v=1}^{V}\sum_{n=1}^{N}\sum_{t=1}^{T} SC_{drvt}.Xdr_{pdrvt} + \sum_{d=1}^{D}\sum_{r=1}^{R}\sum_{n=1}^{r\cup d}\sum_{v=1}^{V}\sum_{t=1}^{T} SC_{mdvt}.Xpd_{pmdvt} \\
& - \Big(MD_{prt(1)} - PE_{prt}.PE_{prt}.USP_{prt} - AD_{prt}\Big).\beta' + \big(AD_{prt} - MD_{prt(1)} + PE_{prt}.USP_{prt}\big).\beta.
\end{aligned} \tag{41}
$$

$$
\begin{aligned}
\text{Max } Z = & \sum_{m=1}^{M}\sum_{t=1}^{T} FC_{mt}.OP_{mt} + \sum_{d=1}^{D}\sum_{t=1}^{T} FC_{dt}.OD_{dt} + \sum_{d=1}^{D}\sum_{m=1}^{M}\sum_{t=1}^{T} FC_{dmt}.\delta_{dmt} + \sum_{r=1}^{R}\sum_{d=1}^{D}\sum_{t=1}^{T} FC_{rdt}.\gamma_{rdt} \\
& + \sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{t=1}^{T} PC_{pmt}.Xp_{pmt} + \sum_{p=1}^{P}\sum_{d=1}^{D}\sum_{t=1}^{T} CHI_{dt}.I_{pdt} + \sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{d=1}^{D}\sum_{v=1}^{V}\sum_{n=1}^{N}\sum_{t=1}^{T} SC_{dmt}.Xpd_{pmdvt} \\
& + \sum_{p=1}^{P}\sum_{d=1}^{D}\sum_{r=1}^{R}\sum_{v=1}^{V}\sum_{n=1}^{N}\sum_{t=1}^{T} SC_{drvt}.Xdr_{pdrvt} + \sum_{d=1}^{D}\sum_{r=1}^{R}\sum_{n=1}^{r\cup d}\sum_{v=1}^{V}\sum_{t=1}^{T} SC_{mdvt}.Xpd_{pmdvt} \\
& - (MD_{prt(4)} - PE_{prt}.PE_{prt}.USP_{prt} - AD_{prt}).\beta' + (AD_{prt} - MD_{prt(4)} + PE_{prt}.USP_{prt}).\beta.
\end{aligned} \tag{42}
$$

$s.t$:

$$AD_{prt} \geq \frac{a_1}{2}.MD_{prt(2)} + (1 - \frac{a_1}{2}).MD_{prt(1)} - PE_{prt}.USP_{prt}. \tag{43}$$

$$AD_{prt} \geq \frac{a_1}{2}.MD_{prt(3)} + (1 - \frac{a_1}{2}).MD_{prt(4)} - PE_{prt}.USP_{prt}. \tag{44}$$

Other constraints (45)

3.2 Model solution method

The study employs a quantitative research methodology, beginning with literature collection via Library Research and online databases of scientific institutions. After reviewing prior research and identifying gaps, a mathematical model was developed. The model's assumptions, objectives, and constraints were defined considering uncertainty, forming a structural framework. Various solution strategies were assessed, leading to the selection of an effective method implemented in GAMS Software, which maintained the correct relationships between variables and constraints. The optimization process involved analyzing three conflicting Objective Functions under a multi-objective framework. The LP Metric Method was applied to achieve coherence among these objectives by calculating their relative distances to ideal values and minimizing the LP Metric. Consequently, the multi-objective problem was transformed into a single objective for effective resolution, yielding the final solution [17].

3.3 Multi-objective model solution method

The LP-Metric Method is one of the most widely applied techniques to address Mult objective issues. The simplicity of the concept and ease of application have been key reasons for attracting considerable attention from many investigators and operational managers. In this technique, each objective function calculates the distance from its optimal value to its ideal value, and these distances are combined to create an overall metric for evaluating solutions [26]. The LP-Metric Method allows for the simultaneous evaluation of all objectives within a single model, thus treating multidimensional models as single-dimensional models, yielding effective and workable solutions for the entire set of objectives. An example of the method's general algebraic formulation is below [13].

$$Z_{total} = \frac{w_{10}(Z_1 - Z_1^{\min})}{Z_1^{\max} - Z_1^{\min}} + \frac{w_{20}(Z_2 - Z_2^{\min})}{Z_2^{\max} - Z_2^{\min}}. \tag{46}$$

In Equation (46), the weight of each objective function is denoted by W_i, and the values $Z_i^{\min}$ and $Z_i^{\max}$ represent the best and worst achievable values for objective function i, respectively. To calculate these values, the model is solved once for minimization and once for maximization of the objective function, taking into account all constraints. The resulting values are then considered as $Z_i^{\min}$ and $Z_i^{\max}$, respectively.

- **Minimization-type objective functions:** To determine Z_i^{min}, the problem is solved in the minimization form of the target objective function, while complying with all constraints, and the resulting value is considered as Z_i^{min}.
- **Maximization-type objective functions:** For this type of functions, to obtain Z_i^{max}, the model is solved in the maximization direction of the objective function, while satisfying all constraints, and the resulting value is considered as Z_i^{max}.
- **Inverse Objective Function Cases:** To obtain Z_i^{max} in minimization problems or Z_i^{min} in maximization problems, the objective function is solved in the opposite direction (i.e., maximization for minimization cases and vice versa), and the resulting value is used in the corresponding calculations.

Once the mathematical model was created, data analysis and performance evaluation followed using GAMS software (version 24.1.2). The model was prepared and executed with required data and parameters. A numerical case was devised to assess the model's output, focusing on uncertainty parameters through sensitivity analysis, which helped evaluate the model's stability and performance in response to changes.

4 Findings

4.1 Model implementation and setup

The study utilized a model executed on GAMS v24.1.2 with an Intel i7-13700H processor and 16 GB of RAM, taking 120 minutes to run all scenarios. A sensitivity analysis was performed to evaluate the model's accuracy, and its performance was assessed using an LP-Metric approach for the multi-objective model. Parameters were set up in GAMS, and various numerical examples were created to test the model's effectiveness across different scenarios, with detailed results provided in a table.

4.2 Details of designed scenarios

Eight distinct methodologies were evaluated and validated for the proposed model utilizing numerous problem indicators. The developed model was run in 8 various scenarios using 3 distinct operational plans that were created based on the sustainability model and included 3 different objective functions, which were derived as follows:

Table 2: Details of Designed Scenarios

Category Type	Number of Problems	m	d	r	n	v	p	t
Small	2	2	2	5,7	4,7	5,8	4	4
Medium	3	3,5	4,6	9,11,14	9,12,15	10,12,15	5,7	5,7
Large	3	5,7	8,10	17,21,25	18,21,25	18,21,25	7,9	7,9

1st Objective—To Minimize Costs Associated with the Economic Component;
2nd Objective—To Minimize the Environmentally Related Negative Impacts of Pollution; and,
3rd Objective—To Increase the Job Market Opportunities for Workers.

4.3 Model performance and results

Table 3 details the scoring of the developed model against problem indicators across eight methodologies and classifies unique cases into three dimensions. It also summarizes the scores measured via problem indicators and categorizes outputs generated from GAMS software based on the initial objectives of the model.

Table 3: Performance of the Developed Model Based on Problem Indicators

Problem		**Indicator Values**							**LP-Metric Results**		
		m	**d**	**r**	**n**	**v**	**p**	**t**	**Obj1 (Million)**	**Obj2 (thousand)**	**Obj3 (Unit)**
Small Scale	**1**	2	2	5	4	5	4	4	15.628	23.618	250
	2	2	2	7	7	8	4	4	18.749	28.225	274
Medium Scale	**3**	3	4	9	9	10	5	5	23.658	31.276	286
	4	3	6	11	12	12	5	5	31.562	38.485	298
	5	5	6	14	15	15	7	7	38.156	37.459	312
Large Scale	**6**	5	8	17	18	18	7	7	46.123	36.458	345
	7	7	8	21	21	21	9	9	64.325	36.967	386
	8	7	10	25	24	25	9	9	69.635	36.541	459

As problem scale increases, total costs and CO_2 emissions rise due to expanded production centers and transportation activities, while job creation and customer service also improve through additional routes and product flows. This highlights the need to balance costs, emissions, and supply for sustainable supply chain management, as higher production is associated with increased emissions. Moreover, larger problem sizes require more computational time and iterations to achieve optimal solutions.

4.4 Solution time and computational complexity

Table 4: Solution Time and Number of Iterations for Each Scenario Based on Model Indices

Problem		**Indicator Values**							**Solution Time**
		m	**d**	**r**	**n**	**v**	**p**	**t**	**Time (Sec)**
Small Scale	**1**	2	2	5	4	5	4	4	23.122
	2	2	2	7	7	8	4	4	28.653
Medium Scale	**3**	3	4	9	9	10	5	5	34.628
	4	3	6	11	12	12	5	5	44.325
	5	5	6	14	15	15	7	7	52.623
Large Scale	**6**	5	8	17	18	18	7	7	78.749
	7	7	8	21	21	21	9	9	109.132
	8	7	10	25	24	25	9	9	135.496

The results show that increasing problem size and model indices leads to longer solution times due to higher complexity from more production and distribution centers and greater demand, requiring additional iterations to reach optimal solutions. Moreover, the effects of these changes on the first through third objective functions are illustrated in Figure 1.

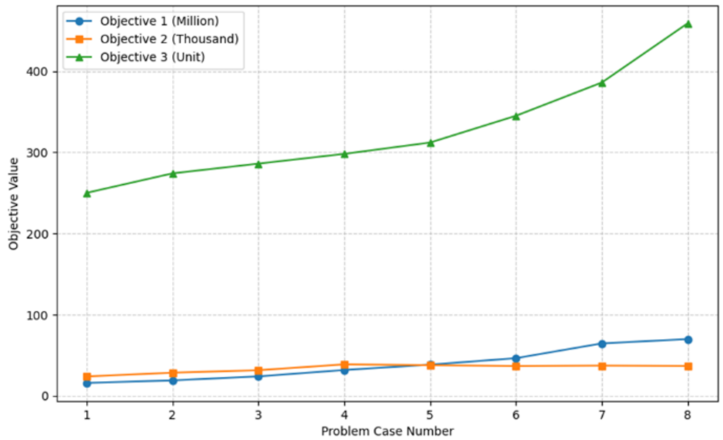

Figure 1: Objective Values Across Problem Scales

As problem size grows, total supply chain cost increases from 15.628 million (small-scale) to 31.562 million (medium-scale) and over 69 million (large-scale) due to higher decision complexity, capacities, and transportation, though the growth rate slows with economies of scale. CO_2 emissions rise from 23.618 thousand to 38.485 thousand and then stabilize at about 36 thousand in large-scale cases, reflecting effective emission control. At the same time, job creation increases steadily from 250 to 312 and 459 jobs as network size expands.

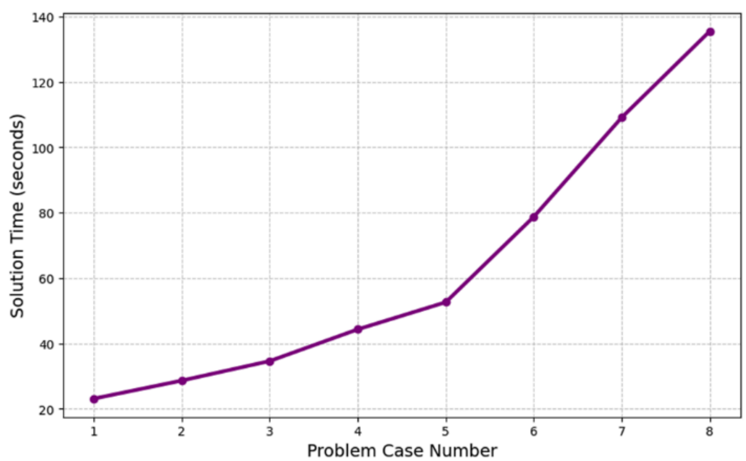

Figure 2: .Solution Time vs Problem Cases

As illustrated in Figure 2, solution times increase with problem size: 23–28 seconds for small-scale, 34–52 seconds for medium-scale, and 78 to over 135 seconds for large-scale problems. This reflects the higher computational complexity caused by larger networks, longer distances, and more decision variables, with scenarios seven and eight showing nonlinear growth and greater sensitivity to size. Despite this increase, the solution times remain reasonable for a complex multi-objective model, and the limited number of comparable models highlights opportunities for broader application and further evaluation.

4.5 Sensitivity analysis

In a sensitivity analysis of a developed mathematical model, critical parameters were systematically varied to assess their impact on model output, specifically the objective function and decision variables. This analysis evaluates the model's stability and reliability by observing the relationships between parameter fluctuations and changes in the objective function value.

4.5.1 Sensitivity analysis on MD_{prt} based on the first objective function

Based on Table 5, the sensitivity analysis of the market demand parameter (MD_{prt}) shows that increases in demand lead to a corresponding rise in the first objective function. Higher demand intensifies production, transportation, and supply activities, thereby increasing total supply chain costs. Overall, the results confirm that market demand has a significant impact on the first objective function, with greater demand directly increasing total network costs.

Table 5: Sensitivity analysis of changes in the first objective function based on demand

Row	**MD_{prt}**	**Obj1 (Million)**
1	50	16.658
2	100	18.526
3	150	23.541
4	200	24.638
5	250	28.547

4.5.2 Sensitivity analysis on MD_{prt} based on the second objective function

The analysis of the MD_{prt} rating index shows that increasing product demand initially leads to higher CO_2 emissions due to greater transportation, network activity, and production operations. As demand reaches higher levels, emissions decline as a result of network reconfiguration and more efficient capacity utilization. This indicates that the optimized supply chain design effectively controls emission growth, ensuring environmental sustainability and preventing uncontrolled increases in pollutants across the supply chain lifecycle.

Table 6: Sensitivity analysis of changes in the second objective function based on demand

Row	**MD_{prt}**	**Obj_2**
1	50	23.618
2	100	25.681
3	150	27.345
4	200	26.931
5	250	26.983

4.5.3 Sensitivity analysis on parameter LF_p

This section analyzes the sensitivity of the minimum product shelf life (LF_p) on the first objective function. The results show that changes in LF_p significantly affect the objective function, with a longer shelf life leading to reduced spoilage and lower costs associated with production and disposal of spoiled goods. As shown in Table 7, the first objective function is highly sensitive to LF_p, indicating that extending product shelf life can effectively reduce operational costs.

Table 7: Sensitivity analysis of Objective 1 based on product lifetime

Row	**(LF_p)**	**Obj1**
1	4	19.935
2	5	19.657
3	6	17.963
4	7	17.532
5	8	16.658

4.5.4 Sensitivity analysis on parameter C_v

Based on Table 8, the sensitivity analysis evaluates the effect of vehicle capacity (C_v) on the first objective function. The results show that increasing vehicle capacity leads to a higher total supply chain cost, as larger vehicles change allocation structures and shipment patterns, resulting in increased production, inventory holding, and transportation costs. Consequently, higher C_v alters the transportation configuration of the network and raises overall operational costs.

Table 8: Sensitivity analysis of changes in the first objective function based on vehicle capacity

Row	(C_v)	Obj1
1	50	16.523
2	100	17.384
3	150	18.296
4	200	22.957
5	250	26.416

4.5.5 Sensitivity analysis on parameter PE_{rpt}

Table 9 examines the sensitivity of the first objective function to changes in retail demand elasticity (PE_{rpt}). The results show that increasing elasticity initially raises total costs due to higher operational and network expenditures from reduced price sensitivity. As demand patterns adjust and allocation strategies improve, these expenditures decline, indicating enhanced operational efficiency. Overall, the model adapts effectively to changes in consumer behavior, enabling improved cost management through demand elasticity adjustments.

Table 9: Sensitivity analysis of objective function changes based on retail demand elasticity

Row	PE_{rpt}	Obj1
1	0.3	16.468
2	0.4	18.545
3	0.5	17.253
4	0.6	15.329
5	0.7	14.746

4.5.6 Sensitivity analysis on parameter CHI_{dt}

Table 10 presents a sensitivity analysis of changes in the inventory holding cost (CHI_{dt}) on the total supply chain cost (Objective 1). The results show that increasing inventory holding costs leads directly to higher total supply chain costs, as greater holding costs raise the cost of inventory on hand. This confirms that inventory levels have a significant impact on the objective function, highlighting the importance of effective inventory management and optimal storage policies to minimize overall supply chain costs.

Table 10. Sensitivity analysis of changes in the first objective function based on inventory holding cost

Table 10: Sensitivity analysis of objective function changes based on retail demand elasticity

Row	CHI_{dt}	Obj1
1	30	16.542
2	40	17.234
3	50	17.968
4	60	21.416
5	70	23.587

4.6 Comparison of model performance in deterministic and uncertain conditions

This section evaluates the model's performance under fully deterministic and highly uncertain input conditions by comparing the corresponding objective function values. After defining the initial parameters and assumptions for each scenario, several experimental test cases were conducted. The resulting outcomes, summarized in Table 11, show the relative performance of each approach and indicate how much better or worse one performs compared to the other under certainty and uncertainty extremes.

Table 11: Comparison of Model Performance in Deterministic and Non-Deterministic Cases

Problem Case	Deterministic Case Obj1 (Million)	Deterministic Case Obj2 (Thousand)	Non-Deterministic Case Obj1 (Million)	Non-Deterministic Case Obj2 (Thousand)
TP1	14.329	24,745	15.628	23.856
TP2	17.263	32,256	18.749	30.541
TP3	22.658	35.476	23,658	32.698
TP4	26.541	47.365	31.562	41.579
TP5	31,296	53,241	38.156	44,983

In comparison, the robust model incurs higher total supply chain costs than the deterministic model, which is more effective at cost minimization. However, the robust programming approach achieves lower CO_2 emissions under demand variability due to its resilience to parameter uncertainty and its improved integration of inventory and material flow management.

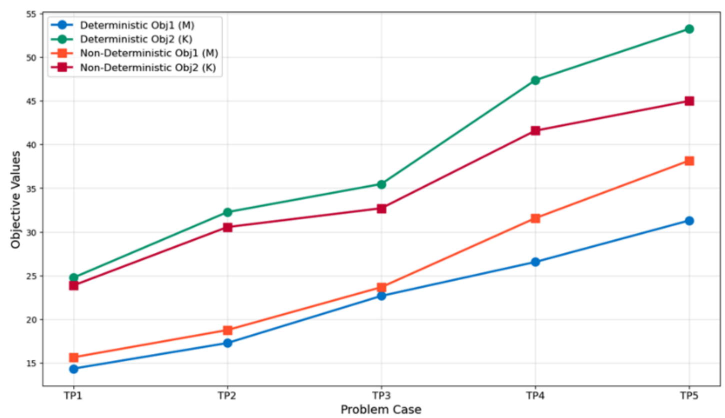

Figure 3: .Comparison of Deterministic vs Non-Deterministic Objective Values

5 Discussion and conclusion

This research presents a powerful multi-objective optimization model designed for developing sustainable perishable food supply chains, taking into account the uncertainty involved in those supply chains. The authors have combined the three pillars of sustainability (economics, environment, and social) such that the model minimizes total supply chain costs and carbon dioxide emissions while maximizing employment opportunities. Uncertainty associated with key operational parameters, such as demand for the product, shelf-life, and mode of transportation to deliver products to market, was modeled using fuzzy trapezoidal numbers under a robust framework of probabilistic programming. Computational results demonstrate that the proposed optimization and robust probabilistic frameworks produce effective trade-offs between conflicting objectives of sustainability and do so by providing stable solutions across varying sizes of the problems examined. Numerical experimentation indicates that, although an increase in supply chain size leads to higher total operating costs and employment opportunity levels, the optimization structure effectively controls the overall increase in carbon dioxide emissions. Additionally, the robust probabilistic modeling formulation provides solutions that are less susceptible to uncertainty than deterministic models, thereby increasing the resiliency and reliability of supply chain decisions.

5.1 Comparison with previous studies

According to previous studies, multi-objective optimization effectively balances the conflicting demands of economic and environmental objectives when designing supply chains [31, 34]. However, this study also addresses sustainability from an additional angle by specifically including a social aspect—the generation of employment—in line with the holistic concept of the triple bottom line [18, 25]. One technical contribution of this research is the development of a new technique that combines robust possibilistic programming with fuzzy trapezoidal numbers as an identifier for epistemic uncertainty. Compared to traditional stochastic approaches [7] or classical fuzzy models [31], the support provided through the new technique leads to a more stable and reliable solution, particularly when there is a lack of precise probabilistic data. This finding aligns with the research of Ghaderi et al. [8], who confirmed the ability of robust possibilistic optimization to enhance solution stability. In contrast to previous research, which mainly focused on biofuel or energy-related supply chains [3, 8], this current research can be applied to the problems associated with food supply chains for perishable goods while also incorporating the explicit social goal of employment generation. While the robust formulation generally leads to slightly higher than deterministic operational costs, the results obtained through the robust formulations demonstrate significant improvements in the overall performance of the supply chain systems.

5.2 Managerial and practical implications

For managers, the new model serves as a hands-on decision-support system for supply chain managers and other decision-makers who need to create cost-effective supply chain networks with minimal environmental impact and with social inclusion as part of their overall strategy and sustainability goals. By explicitly considering operational uncertainty, the model provides additional tools to develop effective strategies that will help decision-makers create more robust and effective strategies to address challenges such as changes in demand, product shelf life, or transportation uncertainty. Additionally, the model allows decision-makers to make decisions by evaluating trade-offs between total cost, CO_2 emissions, and number of jobs generated for various supply chain configurations. Through this feature of the model, managerial decision-making becomes more transparent and, ultimately, better informed by showing how different designs of the supply chain networks will impact economic performance, environmental effects, and job generation. Finally, findings from the modeling efforts indicate that fluctuations in demand and product shelf life are the two most important factors in determining the level of performance of the network; therefore, managers should focus their efforts on enhancing their company's forecasting ability and developing efficient inventory management techniques to minimize waste and operational costs in perishable goods supply chains. Further, the inclusion of jobs within the model allows public policy makers to evaluate the broader social and economic value of supply chain investments and will contribute to achieving sustainable development goals such as SDG8 (Decent Work and Economic Growth) and SDG 12 (Responsible Consumption and Production).

5.3 Theoretical implications

In terms of theoretical contributions to the body of literature, this research will provide new insights into sustainable supply chain design, through the combination of advanced uncertainty modeling techniques and sustainability-based design considerations when designing supply chain networks. To illustrate this, the research will present a method for using robust possibilistic programming in conjunction with multi-objective optimization, to facilitate consideration of economic, environmental and social objectives within a single modelling framework. Another theoretical contribution will be the development of an LP-metric based approach to solving complex real-world problems with uncertain data using fuzzy logic combined with the GAMS solver. The proposed methodology will contribute to the ongoing methodological development of supply chain optimization, specifically in relation to sustainability and uncertainty.

5.4 Research limitations and future directions

While this study contributes to an emerging body of literature examining the simultaneous inclusion of cost, emissions, and social indicators, it has several limitations that present opportunities for future research. The initial limitation is that the current model uses linear relationships to link the three indicators (costs, emissions, and social indicators). In later studies, researchers could investigate the possibility of nonlinear or dynamic formulations to more effectively represent the operational characteristics of perishable supply chains. Another limitation is that the model development was created in the context of a single-period framework. Researchers may consider extending this model to incorporate multi-period or dynamic environments to better characterize the dynamics of both inventory and demand over time. Future studies may also add additional social indicators (such as quality of jobs, worker safety, and regionally equitable) to the model. A third limitation is the empirical context of the case study, which is based on a specific perishable product environment. The ability to apply the model across different industries and geographical regions will help support the generalizability and practical applicability of the model. The use of the LP-metric method to derive compromise solutions may open new avenues of research by comparing the performance of other multi-objective optimization techniques, such as the ε-constraint method, goal programming, and evolutionary algorithms.

5.5 Conclusion

This study focuses on the formulation of a flexible multi-objective optimization model that can be used to establish sustainable distribution and supply chain networks for perishable items under conditions of uncertainty. By combining elements of fuzzy logic with concepts of multi-objective optimization, the authors developed a solution that provides decision-makers with tools for creating economically viable, environmentally sustainable, and socially responsible supply chains. The authors confirmed that their proposed method results in stable and repeatable solutions despite the presence of uncertainty, allowing managers to design supply chain distribution networks that are resilient to change, control environmental impacts, and foster job creation. The authors argue that robust fuzzy possibilistic frameworks provide significantly more flexible and robust models than deterministic frameworks when addressing problem areas related to either incomplete or ambiguous values. Lastly, the authors conclude their discussion by detailing how their proposed approach provides both theoretical contributions to the field of sustainable supply chain research and practical applications for managers engaged in perishable product logistics within an uncertain business environment.

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