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An uncertain sustainable supply chain network design for regulating greenhouse gas emission and supply chain cost

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ABSTRACT

The increasing global concern for sustainability in supply chain management is driven by stricter government regulations addressing environmental pollution and social injustice. This has led to a growing emphasis on integrating sustainability into supply chain practices. However, there is limited research on incorporating all three dimensions of sustainability (economic, environmental, and social) into supply chain management. This study presents a mixed-integer linear programming model for designing an uncertain supply chain network design that aims to minimize overall costs (establishment, production, and transportation/routing costs) while considering carbon emissions and a few social factors simultaneously. The study considers sustainable aspects of decision-making process and utilizes chance-constrained programming to address uncertainties. The proposed model attempts to maintain balanced flow levels across all stages of the network, optimizing the utilization of raw materials and production. The proposed optimization model is a cost minimization model that also tries to minimize greenhouse gas emissions throughout the entire network. A greedy based heuristic is provided for dealing with larger instances of the given decision making problem. Additionally, sensitivity analysis has also been carried out to explore the impact of various parameters involved.

1. Introduction

Supply chain management plays a crucial role in the success of businesses operating in today's dynamic and complex global marketplace. As organizations strive to minimize costs, maximize efficiency, and meet growing consumer demands, the need for sustainable practices within the supply chain has become inevitable. A sustainable supply chain aims to balance economic, environmental, and social aspects while ensuring long-term viability and resilience.

The design of a sustainable supply chain network involves strategic decisions related to the location of facilities, distribution, transportation routes, and inventory management. By considering sustainability factors such as carbon emissions, waste reduction, renewable energy utilization, and ethical sourcing, organizations can create networks that are not only efficient but also environmentally and socially responsible. Several new concepts and practices like green logistics (Rodrigue et al., 2001), reverse logistics (Carter and Ellram, 1998), sustainable supply chain management (Carter and Liane Easton, 2011), have been developed and implemented in order to attain a balance between the economic, environmental and social factors.

One of the key challenges in achieving sustainability within the supply chain lies in managing uncertainties. Uncertainties, arising from factors such as demand fluctuations, market dynamics, resource availability, and regulatory changes, can significantly impact supply chain performance and sustainability goals. To achieve an optimal design, it is essential to develop sophisticated optimization models that take into account the uncertain nature of supply chain operations. These models incorporate probabilistic techniques (Mehrbakhsh and Ghezavati, 2020), scenario analysis (Mohammed et al., 2017), and simulation (Xie et al., 2011) to assess various possible outcomes and strategies to reduce risks and improve overall performance to determine the optimal allocation of resources, inventory levels, production schedules, and transportation routes under different demand scenarios, cost structures, and sustainability constraints. To address these uncertainties, a comprehensive and proactive approach is required, which encompasses the design, optimization, and management of sustainable supply chain networks.

This research paper proposes a holistic multi-objective optimization framework for designing an uncertain supply chain network considering sustainable practices. The key objectives include reduction of supply

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chain costs and environmental impacts, enhancing social responsibility, and achieving long-term success in a rapidly changing business landscape. To handle uncertainties, chance-constrained programming has been utilized and a greedy based heuristic has also been provided to demonstrate the computational intelligence of this research.

The overview of this paper is as follows: Section 2 represents the literature review, that includes a brief description of the past studies and the research gap identified in this study. The problem formulation and description for a sustainable four-stage supply chain network is presented in Section 3. Section 4 presents the numerical illustration of the proposed optimization model. Section 5 presents the heuristic based on greedy algorithm. Section 6 provides a discussion on importance and managerial implications of the model based on the results obtained. The paper is concluded in Section 7.

2. Literature review

Supply chain network design has emerged as a crucial strategic decision-making exercise that aims to optimize the facility location, flow of goods, information, and finances across various stages, from raw material acquisition to end-product delivery (Kumar, 2022). Traditional supply chains primarily focused on the forward supply chain (Melo et al., 2009). However, evolving market dynamics and increasing environmental concerns have highlighted the importance of considering both forward and reverse supply chains in network design (Carter and Ellram, 1998). The reverse supply chain involves processes such as product returns, re-manufacturing, recycling, and disposal. The integration of forward and reverse supply chains forms the foundation for a closed-loop supply chain (CLSC), that emphasizes the cyclical nature of resource utilization and recovery, thereby reducing waste and enhancing sustainability (Govindan et al., 2015). In recent times, there has been a rise in the literature on CLSC that combines reverse logistics into traditional forward supply chain. The review article by Govindan and Soleimani (2017), presented a detailed discussion on reverse logistics and closed-loop supply chain network design (SCND). Mohammed et al. (2017) developed a multi-period, multi-product, capacitated CLSC network design problem. Zhen et al. (2019) presented a stochastic bi-objective mixed integer programming problem for a CLSC to optimize cost and environmental impact and an efficient solution method is also provided to find the solution quickly. Devika et al. (2014) and Golpîra and Javanmardan (2022) proposed a general CLSC in which the goals were to reduce cost, minimize overall environmental effects, and maximize social benefits. Kumar and Kumar (2023) proposed a general forward and reverse SCND pertaining to the three dimensions of sustainability (economic, environmental and social).

Sustainable supply chain management.

Sustainable supply chain management (SSCM) has gained interest due to growing relationship between business operations and ecological, social, and economic dimensions. This approach encompasses three essential aspects of sustainability, viz. environmental, social, and economic (Carter and Liane Easton, 2011). The environmental dimension involves reducing carbon footprints, minimizing waste, conserving resources, and adopting cleaner production processes. The social dimension focuses on ensuring fair labor practices, upholding human rights, and contributing positively to local communities. Finally, the economic dimension focuses on maintaining profitability. Therefore, SSCM requires a combined consideration of these dimensions to achieve long-term success and resilience (Wang et al., 2020).

Literature reviews conducted by Terouhid et al. (2012) and Olatunji et al. (2019) proposed frameworks to identify the main characteristics of the sustainable supply chain and suggested that a sustainable supply chain should focus on environmental and social dimensions as well in addition to the economic aspect of sustainability. The literature review by Panigrahi et al. (2018), presented a theoretical perspective of a sustainable supply chain network. The literature review conducted by Fang et al. (2020), focused on the optimization of logistics network for reducing carbon emissions. The review by Eskandarpour et al. (2015), mainly focused on environmental and social factors of a sustainable SCND.

The key to ensuring environment sustainability is to reduce greenhouse gases (GHGs) emission. In a supply chain, transportation can be considered as one of the biggest factors of GHGs emission. Gong et al. (2017) presented a transportation mode selection based supply chain network design for minimizing cost and carbon emissions. Nurjanni et al. (2017) developed a green supply chain network design for reducing negative impacts of industrialization on environment. Ahmadini et al. (2021) proposed a multi-item inventory model for reducing GHGs emission. A bi-objective optimization approach based SCND was proposed by Kuo et al. (2018) for meeting the objectives of low cost and low carbon emission.

Uncertainty in sustainable supply chain management.

Uncertainty in a supply chain network may arise due to demand fluctuations, supply disruptions, changing regulations, and market volatility. In real life problems, managing uncertainties plays a crucial role in ensuring sustainability within a supply chain network. Mehrbakhsh and Ghezavati (2020) developed an optimization model to reduce GHGs emission while maximizing production costs in a three level supply chain with suppliers, manufacturers, and demand zones with uncertain demand. Rezaee et al. (2017) presented a stochastic model for designing a green supply chain network considering uncertainty in product demand and carbon pricing.

Using a novel bi-objective optimization approach, Tavana et al. (2021) presented a MILP model to solve the location-inventory-routing problems in green supply chains with minimum carbon emissions under uncertainty. Zheng et al. (2020) proposed a study concerning a production planning and scheduling problem for a sustainable supply chain considering uncertainty in demand, inventory management capacity, service level and CO_2 emission constraint. Das and Shaw (2017) proposed an uncertain SCND model that minimizes total cost and finds optimal number of plants, warehouses and flow of materials throughout the supply chain network by considering various CO_2 emissions and social consideration. Mehrbakhsh and Ghezavati (2020) proposed an optimization model for optimizing production cost and GHGs emission in three level supply chain while considering uncertain demand.

Haddadsisakht and Ryan (2018) provided a three stage stochastic model for designing a CLSC network accommodating uncertainty in product demand and carbon tax. Yu and Solvang (2020) provides a new fuzzy-stochastic multi-objective model for closed-loop SCND considering various uncertainties. Mohammed et al. (2017) proposed an optimization model for a multi-period, multi-product, closed-loop SCND that considers product demand and return rates to be uncertain. Golpîra and Javanmardan (2022) focused on a closed-loop SCND based on a multi-objective optimization approach for combining social, environmental, and economic sustainability goals while considering uncertain demand. A robust optimization approach was employed to solve the problem.

Contribution.

Table 1 provides a comparison of this study with recent studies on sustainable SCND. The comparison is based on different aspects; viz. supply chain network structure, modeling type, number of objective functions, parameter uncertainty, sustainability aspects, and solution methodology. Table 1 demonstrates that, most of the research on sustainable SCND accommodate deterministic parameters. Moreover, majority of the sustainable SCND problems were modeled using MILP formulations. To address the inherent complexities in the optimization problems (Elhedhli and Merrick, 2012; Yavari and Geraeli, 2019; Mehrbakhsh and Ghezavati, 2020; Govindan et al., 2015), several techniques like exact methods, Lagrangian, heuristics and metaheuristics approaches have been frequently utilized.

This study represents a multi-objective mixed-integer linear programming based optimization model for a four-stage forward supply chain that simultaneously assesses the three dimensions of

Table 1
Literature on sustainable SCND and contribution of proposed study.

Article	Network type	Parameters	Objective F^n		Mathematical model type	Sustainability aspects consideration			Methodology	Solver/ Solution procedure
			Single-Objective	Multi-Objective		Economic	Environmental	Social		
Mohammed et al. (2017)	CL	Stochastic and Robust	×	✓	MILP	✓	✓	×	Exact	GAMS and ILOG CPLEX.
Mehrbakhsh and Ghezavati (2020)	CL	Stochastic	×	✓	MILP	✓	✓	×	Exact	NSGA-II,
Elhedhli and Merrick (2012)	F	Deterministic	✓	×	MILP	✓	✓	×	Heuristic	LR
Kannan et al. (2012)	R	Deterministic	✓	×	MILP	✓	✓	×	Exact	LINGO 8
Rezaee et al. (2017)	F	Stochastic	✓	×	MILP	✓	✓	×	Exact	CPLEX
Kuo et al. (2018)	F	Deterministic	×	✓	MILP	✓	✓	×	Exact	Pareto frontier method
Mota et al. (2015)	CL	Deterministic	×	✓	MILP	✓	✓	✓	Exact	e-constraint method
Nurjanni et al. (2017)	CL	Deterministic	×	✓	MILP	✓	✓	×	Exact	CPLEX
Tavana et al. (2021)	F	Stochastic	×	✓	MILP	✓	✓	×	Exact	CPLEX
Zheng et al. (2020)	F	Stochastic	×	✓	MILP	✓	✓	×	Heuristic	LR
Haddadsisakht and Ryan (2018)	CL	Stochastic and Robust	✓	×	MILP	✓	✓	×	Heuristic	–
Ahmadini et al. (2021)	–	Deterministic	×	✓	MOFP, Fuzzy, Goal	✓	✓	×	Exact	LINGO
Devika et al. (2014)	CL	Deterministic	×	✓	MILP	✓	✓	✓	Meta-heuristic	AICA, VNS
Esmaeilian et al. (2023)	CL	Deterministic	×	✓	MILP	✓	✓	✓	Exact	–
Saffar et al. (2014)	CL	Deterministic	×	✓	MILP, Fuzzy	✓	✓	×	Exact	NSGA-II
Yavari and Geraeli (2019)	CL	Deterministic and Robust	×	✓	MILP	✓	✓	×	Heuristic	YAG
Golpîra and Javanmardan (2022)	CL	Robust	✓	×	MILP	✓	✓	×	Exact	–
Gong et al. (2017)	F	Deterministic	×	✓	MILP	✓	✓	×	Exact	Perato optimal solution method
Zhen et al. (2019)	CL	Stochastic	×	✓	MILP	✓	✓	×	Heuristic	LR
Wang et al. (2020)	F	Deterministic	×	✓	MILP	✓	✓	×	Exact	Pareto Optimal solution method
Yu and Solvang (2020)	CL	Stochastic	×	✓	MILP and Fuzzy	✓	✓	×	Heuristic	SAAWN for pereto optimal solution
Govindan et al. (2015)	F	Stochastic	×	✓	MILP	✓	✓	×	Meta-heuristic	AMOEMA and AMOVNS
Mehrbakhsh and Ghezavati (2020)	F	Stochastic	×	✓	MILP	✓	✓	×	Heuristic	MOPSO and NSGAII
Diabat and Al-Salem (2015)	F	Stochastic	✓	×	MILP	✓	✓	×	Heuristic	GAMS and GA
Mogale et al. (2022)	CL	Deterministic	×	✓	MILP	✓	✓	×	Meta-heuristic	NSGAII

(continued on next page)

Table 1 (*continued*)

Article	Network type	Parameters	Objective F^n		Mathematical model type	Sustainability aspects consideration			Methodology	Solver/ Solution procedure
			Single-Objective	Multi-Objective		Economic	Environmental	Social		
This Article	F	Stochastic	×	✓	MILP	✓	✓	✓	Heuristic	LINGO 19 and Greedy-based algorithm

CL- Closed-loop; R- Reverse; F- Forward; MILP- Mixed integer linear programming; MOFP- Multi objective fractional programming; LR- Lagrangian relaxation; NSGA- Non-dominated sorting genetic algorithm; AICA- Adapted imperialist competitive algorithm; VNS- Variable neighborhood search algorithm; SAAWN- Sample average approximation based weighting method; AMOEMA- Adapted multi-objective electromagnetism mechanism algorithm; AMOVNS- Adapted multi-objective variable neighborhood search; MOPSO- Multi-objective particle swarm optimization.

sustainability, viz. economic, environmental and social, while accounting for different type of uncertainties. The study considers sustainable aspects of decision-making process and utilizes chance constrained programming to address uncertainties. A greedy based heuristic is also developed to solve the proposed model for demonstrating the computational intelligence of this research.

3. Problem formulation and description

Consider a four-stage supply chain, as illustrated in Fig. 1. It comprises of suppliers, manufacturing centers (MCs), distribution centers (DCs) and end-users. Let I, J, K and L represent the set of all suppliers, manufacturing centers, distribution centers and end-users respectively. A supplier $i \in I$ can send materials directly to a single manufacturing center $j \in J$ or multiple manufacturing centers $j_1, j_2 \dots j_n \in J$. Similarly, a manufacturing center $j \in J$ can purchase the material from a single supplier $i \in I$ or multiple suppliers $i_1, i_2 \dots i_m \in I$ and can send the finished products to a single distribution center $k \in K$ or multiple distribution centers $k_1, k_2 \dots k_o \in K$. A distribution center $k \in K$ may receive the product from a single manufacturing center $j \in J$ or multiple manufacturing centers $j_1, j_2 \dots j_n \in J$ and may send it to multiple end-users $l_1, l_2 \dots l_p \in L$.

In this section, we formulate a new model for optimizing establishment, production and variable costs and carbon emissions in a four-stage supply chain network including suppliers, *MCs*, *DCs* and end-users. In this model, capacities of different types of facilities viz. suppliers, manufacturing centers and distribution centers and demand of end-users have been considered to be uncertain and the routing decisions from suppliers to end-users are dependent on flow of product. This model is defined for a single product and is a single period optimization model. Fig. 2 presents the conceptual outline of the proposed model. We provide next the assumptions of the model, followed by individual model components and definitions of parameters and decision variables involved. This section then describes complete optimization model that combines two objective functions aimed at minimizing economic costs and environmental costs within the supply chain. Later, chance constrained programming is applied on the given optimization problem to deal with uncertain parameters involved. Application of chance constrained programming produces deterministic equivalents of the uncertain parameters. A modified version of the proposed optimization model after the application of chance constrained programming is then provided towards the end of this section.

3.1. Assumptions

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- Forward supply chain has been considered as a four stage problem including suppliers, manufacturing centers, distribution centers and end-users.

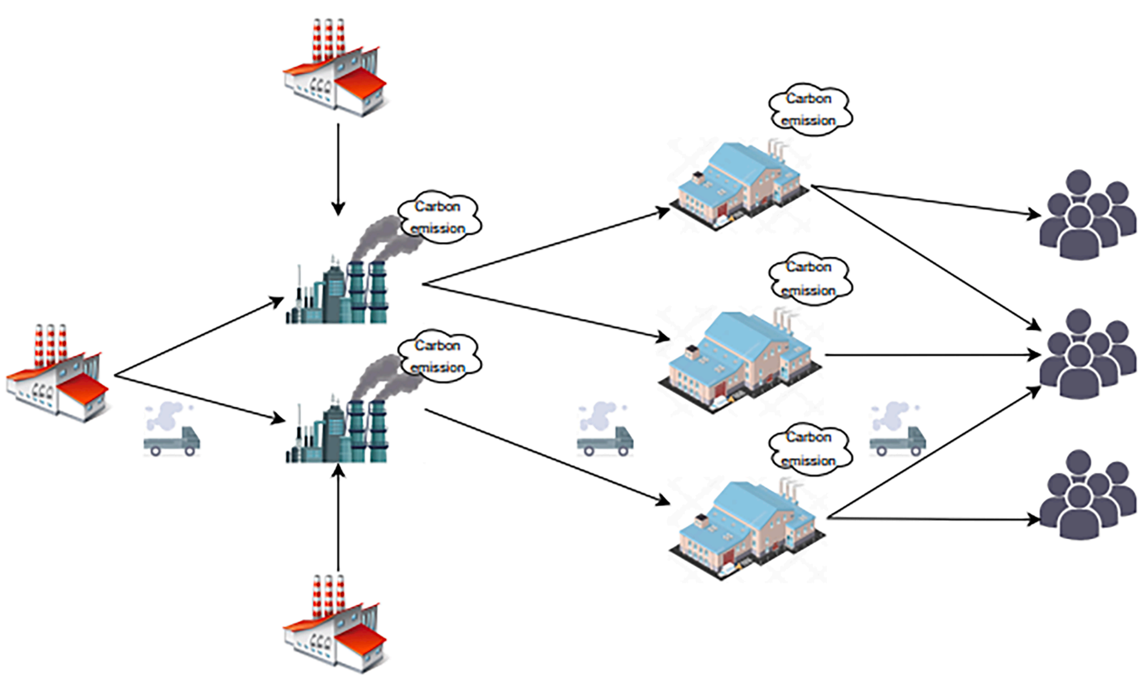

Fig. 1. A four-stage supply chain network design.

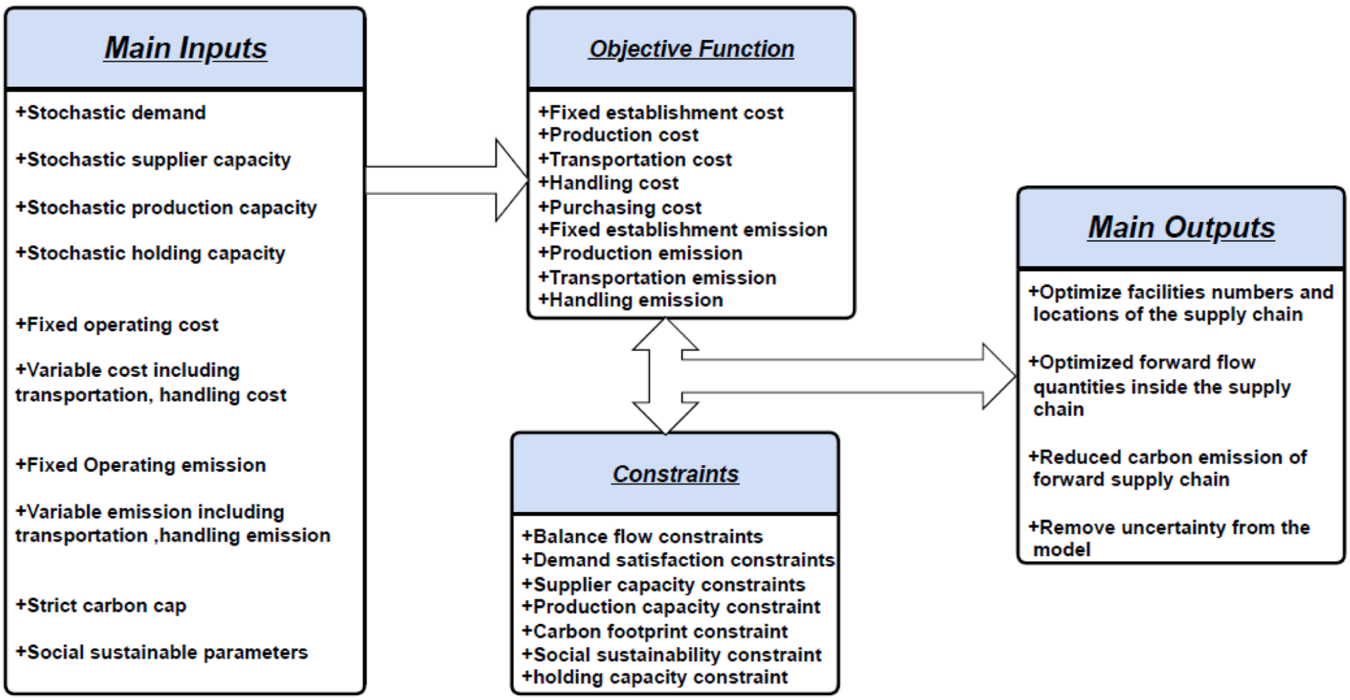

Fig. 2. A conceptual outline of the proposed model.

- The potential locations of all facilities and cost parameters are predetermined.
- Supply chain is concerned with a single product and the SCND is proposed for a single period.
- Neither manufacturing center nor distribution center may retain inventory.
- Demand must be fulfilled.
- Capacities of facilities are considered as uncertain.
- Demand of end-users is uncertain.
- Single unit of product is produced from a single unit of raw material.
- All random variables considered in this study are assumed to follow normal distribution. According to the Central Limit Theorem, sample averages (or means) of a large number of independent and identically distributed random variables, regardless of the shape of original distribution, are approximated by a normal distribution. This property makes normal distribution a natural choice for modeling uncertainties. Additionally, normal distribution has been regarded as an ideal distribution for uncertain variables in real-life scenarios (Li et al., 2008). Moreover, normal distribution helps in keeping the computational complexity to be low in chance-constrained programming (Nazemi and Tahmasbi, 2013) that has been utilized to deal with uncertainty in this study.
- Lead time in the system is zero.
- Capacities of transportation vehicles are unlimited.

3.2. Economic and Environmental dimensions of sustainability

The objective function in this optimization problem comprises two fundamental components, each representing a critical aspect of the decision-making process. The first objective function represents the total supply chain cost, including the operating cost of MCs and DCs, as well as the variable costs associated with purchasing, production, transportation and handling activites. Define F_j^m and F_k^d as fixed operating cost of manufacturing center $j \in J$ and distribution center $k \in K$ respectively. Further, assume VC_{ij}^a be the variable cost (including purchasing of raw-material from the suppliers, transportation and handling costs) for a unit of raw-material from supplier i to manufacturing center j; $\forall \; i \in I, j \in J$, VC_{jk}^b be the variable cost (including production, transportation and handling costs) for a unit of product from manufacturing center j to distribution center k; $\forall \; j \in J, \; k \in K$ and VC_{kl}^c be the variable cost (including transportation and handling costs) for a unit of product from distribution center k to end-user l; $\forall \; k \in K, \; l \in L$. Further, define a binary decision variable α_j^m that takes the value of 1 if manufacturing center j is open and 0 otherwise; $\forall j \in J$, and another binary variable β_k^d that takes the values of 1; if distribution center k is open and 0 otherwise; $\forall \; k \in K$. Consider Xsm_{ij} be the variable that captures the quantity of raw-material shipped from supplier i to manufacturing center j; $\forall \; i \in I$, $j \in J$, Xmd_{jk} be the variable that accounts for the quantity of product shipped from manufacturing center j to distribution center k; $\forall \; j \in J$, $k \in K$ and Xde_{kl} be the variable describing the quantity of product shipped from distribution center k to end-user l; $\forall \; k \in K, \; l \in L$. Then, the economic dimension of sustainability defined as total supply chain cost is captured by the following expression:

$$\sum_{j\in J} F_j^m \alpha_j^m + \sum_{k\in K} F_k^d \beta_k^d + \sum_{i\in I}\sum_{j\in J} VC_{ij}^a Xsm_{ij} + \sum_{j\in J}\sum_{k\in K} VC_{jk}^b Xmd_{jk} + \sum_{k\in K}\sum_{l\in L} VC_{kl}^c Xde_{kl}$$

The second objective function focuses on environmental sustainability and is based on quantifying the total emissions generated across the supply chain including the fixed operating emission from MCs and DCs, and the variable emission associated with the production, transportation and handling. These emissions account for CO_2 emissions from different supply chain operations. Define E_j^m and E_k^d be the fixed operating emission of manufacturing center $j \in J$ and distribution center $k \in K$ respectively. Further, consider VE_{ij}^a be the variable emission (including transportation and handling emission) for a unit of raw-material from supplier i to manufacturing center j; $\forall \; i \in I, \; j \in J$, VE_{jk}^b be the variable emission (including production, transportation and handling emission) for a unit of product from manufacturing center j to distribution center k; $\forall \; j \in J, \; k \in K$, and VE_{kl}^c be the Variable emission (including transportation and handling emission) for a unit of product from distribution center k to end-users l; $\forall \; k \in K, \; l \in L$. The environmental dimension of sustainability defined as total emissions across supply chain is captured by the following expression:

$$\sum_{j\in J}E_j^m\alpha_j^m+\sum_{k\in K}E_k^d\beta_k^d+\sum_{i\in I}\sum_{j\in J}VE_{ij}^aXsm_{ij}+\sum_{j\in J}\sum_{k\in K}VE_{jk}^bXmd_{jk}+\sum_{k\in K}\sum_{l\in L}VE_{kl}^cXde_{kl}$$

The overarching optimization goal is achieved by combining these two objectives, resulting in a comprehensive approach that balances both economic efficiency and environmental impact. The objective of the policy maker would be to minimize total supply chain cost and carbon emission.

The optimization problem is subject to a set of constraints that ensure the feasibility and sustainability of the solution.

3.3. Social dimension of sustainability

Incorporating social sustainability concerns in the decision making process ensures businesses to act in ways that are advantageous to the society. In this study, social sustainability is attributed to the regulation of training given to suppliers and complaints of end-users. By adhering to these social sustainability restrictions, the optimization process tries to foster equitable treatment of workers and promote safe and ethical sourcing practices. Equations given below capture the social sustainability constraints in the proposed optimization model:

$$\sum_{i\in I}\left(S_i^T\sum_{j\in J}Xsm_{ij}\right)\leqslant Time^{Max}$$

$$\sum_{l\in L}\left(Ac_l^e\sum_{k\in K}Xde_{kl}\right)\leqslant Ac^{max}D^{Total}$$

where, $S_i^T;\forall\ \ i\in I$ is a parameter that represents average annual training time given to the i^{th} supplier. The annual training of suppliers ensures the adherence of the suppliers to social sustainability practices, e.g. no gender discrimination, no bounded labor and no child labor involved at suppliers end. Training suppliers on social sustainability practices reflects a commitment towards social ethics. It demonstrates a proactive approach to address and prevent unethical practices such as discrimination, forced labor, and child labor. $Time^{max}$ is the maximum time allowed for the training of suppliers. Therefore, the first equation places restriction on the time for providing training to suppliers.

Ac_l^e is the average annual number of complaints lodged by l^{th} end-user with respect to the unit product; $\forall\ \ l\in L$, Ac^{max} is the maximum number complaints that can be handled in a given time period and D^{Total} represents the total demand from all end-users. Therefore, second equation places a restriction on maximum number of complaints to be received from end-users. This constraint indirectly reduces customer complaints and demonstrates a commitment towards ethical business practice and customer service.

3.4. Flow Balancing

A consistent flow throughout the supply chain is to be maintained to ensure that the quantity of the product entering a node equals the quantity leaving it. Maintaining flow balancing in the supply chain network ensures the interconnected nature of the network. Following set of equations describe the product balance flow in the supply chain:

$$\sum_{i\in I}Xsm_{ij}=\sum_{k\in K}Xmd_{jk}\quad\forall j\in J$$

$$\sum_{j\in J}Xmd_{jk}=\sum_{l\in L}Xde_{kl}\quad\forall k\in K$$

3.5. Operational facilities

It is inevitable to decide the maximum number of facilities that should remain open in the entire supply chain network to ensure appropriate utilization of limited budget. The decision maker may place an upper limit on the number of facilities (MCs and DCs) that can be operational for managing limited resources judiciously. The following set of equations put a limit on the number of open facilities (MCs and DCs):

$$\sum_{j\in J}\alpha_j^m\leqslant U_m$$

$$\sum_{k\in K}\beta_k^d\leqslant U_d$$

where, U_m and U_d represent maximum number of operational manufacturing centers and distribution centers respectively.

3.6. Capacity management

Management of capacities of facilities is required to prevent over-utilization and ensure efficient operations of production, storage, and distribution centers. Capacity restrictions are imposed on suppliers, MCs, and DCs to safeguards against operational inefficiencies and congestion. These capacities are assumed to be uncertain in the given decision making problem. The equations below describe the capacity constraints for suppliers, MCs and DCs:

$$\sum_{j\in J}Xsm_{ij}\leqslant S_i\quad\forall i\in I$$

$$\sum_{k\in K}Xmd_{jk}\leqslant P_j\alpha_j^m\quad\forall j\in J$$

$$\sum_{l\in L}Xde_{kl}\leqslant W_k\beta_k^d\quad\forall w\in W$$

where, S_i represents uncertain supplying capacity of supplier $i\in I$, P_j represents uncertain production capacity of manufacturing center $j\in J$ and W_k represents uncertain holding capacity of distribution center $k\in K$.

3.7. Regulating Carbon emission

Regulation of carbon footprints is needed for promoting ecologically conscious decision. By limiting the total emissions associated with transportation, handling and operations, the decision aligns with emission reduction goals. The equation given below restricts the total carbon emissions:

$$\sum_{j\in J}E_j^m\alpha_j^m+\sum_{k\in K}E_k^d\beta_k^d+\sum_{i\in I}\sum_{j\in J}VE_{ij}^aXsm_{ij}+\sum_{j\in J}\sum_{k\in K}VE_{jk}^bXmd_{jk}+\sum_{k\in K}\sum_{l\in L}VE_{kl}^cXde_{kl}\leqslant C^{total}$$

where, C^{total} represents maximum carbon emission allowed.

3.8. End-user demand

To ensure customer satisfaction, timely delivery of customer orders should be made. The quantity of product reaching the end-users should satisfy the customer requirement. In the given decision problem, the end-user demand has been assumed to be uncertain. The set of equations given below have been used to meet the demand of end-users:

$$\sum_{k\in K}Xde_{kl}\geqslant D_l\ \forall l\in L$$

$$\sum_{l\in L}D_l=D^{total}$$

where, D_l represents uncertain demand of end-user $l\in L$.

3.9. Optimization model

NotationsDescription of indices

Index	Definitions
I	Index set for suppliers; $\forall\ i \in I$.
J	Index set for manufacturing Centers; $\forall\ j \in J$.
K	Index set for distribution centers; $\forall\ k \in K$.
L	Index set for end-users; $\forall\ l \in L$.

ParametersDescription of parameters

Parameter	Definitions
F_j^m	Fixed operating cost of manufacturing center j; $\forall\ j \in J$.
F_k^d	Fixed operating cost of distribution center k; $\forall\ k \in K$.
VC_{ij}^a	Variable cost (including purchasing of raw-material from the suppliers, transportation and handling costs) for a unit of raw-material from supplier i to manufacturing center j; $\forall\ i \in I, j \in J$.
VC_{jk}^b	Variable cost (including production, transportation and handling costs) for a unit of product from manufacturing center j to distribution center k; $\forall\ j \in J, k \in K$.
VC_{kl}^c	Variable cost (including transportation and handling costs) for a unit of product from distribution center k to end-user l; $\forall\ k \in K, l \in L$.
E_j^m	Fixed operating emission of manufacturing center j; $\forall\ j \in J$.
E_k^d	Fixed operating emission of distribution center k; $\forall\ k \in K$.
VE_{ij}^a	Variable emission (including transportation and handling emissions) for a unit of raw-material from supplier i to manufacturing center j; $\forall\ i \in I, j \in J$.
VE_{jk}^b	Variable emission (including production, transportation and handling emissions) for a unit of product from manufacturing center j to distribution center k; $\forall\ j \in J, k \in K$.
VE_{kl}^c	Variable emission (including transportation and handling emissions) for a unit of product from distribution center k to end-user l; $\forall\ k \in K, l \in L$.
S_i	Uncertain supplying capacity of supplier i; $\forall\ i \in I$.
P_j	Uncertain production capacity of manufacturing center j; $\forall\ j \in J$.
W_k	Uncertain holding capacity of distribution center k; $\forall\ k \in K$.
D_l	Uncertain demand of end-user l; $\forall\ l \in L$.
π	Cost per unit of carbon emission.
S_i^T	Average annual training time given to the i^{th} supplier; $\forall\ i \in I$.
$Time^{max}$	Maximum time allowed for the training of suppliers.
Ac_l^e	Average annual number of complaints by l^{th} end-user with respect to the unit product; $\forall\ l \in L$.
Ac^{max}	Maximum acceptable complaints from end-users with respect to the unit product.
C^{total}	Maximum carbon emission allowed for an organization.

Parameter	Definitions
D^{Total}	Total demand from the end-users.

Decision variables Decision variables

Binary variable	Definition
α_j^m	1; if manufacturing center j is open; 0 otherwise; $\forall j \in J$.
β_k^d	1; if distribution center k is open; 0 otherwise; $\forall\ k \in K$.

Other variables	Definition
Xsm_{ij}	Quantity of material shipped from supplier i to manufacturing center j; $\forall\ i \in I, j \in J$.
Xmd_{jk}	Quantity of product shipped from manufacturing center j to distribution center k; $\forall\ j \in J, k \in K$.
Xde_{kl}	Quantity of product shipped from distribution center k to end-user l; $\forall\ k \in K, l \in L$.

Objective The aim is to minimize the total cost of the network as a whole, which includes the costs associated with operating, production, and transportation and CO_2 emission cost.

Minimize Total Cost ($Z = Z_1 + \pi Z_2$)

$$where,\ Z_1 = \sum_{j\in J} F_j^m \alpha_j^m + \sum_{k\in K} F_k^d \beta_k^d + \sum_{i\in I}\sum_{j\in J} VC_{ij}^a Xsm_{ij} + \sum_{j\in J}\sum_{k\in K} VC_{jk}^b Xmd_{jk} + \sum_{k\in K}\sum_{l\in L} VC_{kl}^c Xde_{kl}$$

$$and,\ Z_2 = \sum_{j\in J} E_j^m \alpha_j^m + \sum_{k\in K} E_k^d \beta_k^d + \sum_{i\in I}\sum_{j\in J} VE_{ij}^a Xsm_{ij} + \sum_{j\in J}\sum_{k\in K} VE_{jk}^b Xmd_{jk} + \sum_{k\in K}\sum_{l\in L} VE_{kl}^c Xde_{kl}$$

Subjected to the constraints

$$\sum_{j\in J} Xsm_{ij} \leqslant S_i \quad \forall i \in I \tag{1}$$

$$\sum_{i\in I} Xsm_{ij} = \sum_{k\in K} Xmd_{jk} \quad \forall j \in J \tag{2}$$

$$\sum_{k\in K} Xmd_{jk} \leqslant P_j \alpha_j^m \quad \forall j \in J \tag{3}$$

$$\sum_{j\in J} Xmd_{jk} = \sum_{l\in L} Xde_{kl} \quad \forall k \in K \tag{4}$$

$$\sum_{l\in L} Xde_{kl} \leqslant W_k \beta_k^d \quad \forall k \in K \tag{5}$$

$$\sum_{k\in K} Xde_{kl} \geqslant D_l \ \forall l \in L \tag{6}$$

$$\sum_{l\in L} D_l = D^{total} \tag{7}$$

$$\sum_{j\in J} \alpha_j^m \leqslant U_m \tag{8}$$

$$\sum_{k\in K} \beta_k^d \leqslant U_d \tag{9}$$

$$\sum_{i\in I} (S_i^T \sum_{j\in J} Xsm_{ij}) \leqslant Time^{Max} \tag{10}$$

$$\sum_{l\in L} (Ac_l^e \sum_{k\in K} Xde_{kl}) \leqslant Ac^{max} D^{Total} \tag{11}$$

$$\sum_{j\in J} E_j^m \alpha_j^m + \sum_{k\in K} E_k^d \beta_k^d + \sum_{i\in I}\sum_{j\in J} VE_{ij}^a Xsm_{ij} + \sum_{j\in J}\sum_{k\in K} VE_{jk}^b Xmd_{jk} + \sum_{k\in K}\sum_{l\in L} VE_{kl}^c Xde_{kl} \leqslant C^{total} \tag{12}$$

$$\alpha_j^m, \beta_k^d = \{0, 1\}; \quad Xsm_{ij}, Xmd_{jk}, Xde_{kl} \geqslant 0 \tag{13}$$

Objective function 1 (Z_1) represents the first objective function, which minimizes overall cost incurred in the network capturing the costs associated with establishment, production, and transportation/routing costs activities. Objective function 2 (Z_2) expresses the second objective function, which minimizes the total carbon emissions inthe network resulting from establishment, production, and transportation/routing costs activities. Constraint 1 ensures that the flow of material from the supplier to manufacturing center will not exceed the supplier capacity. Constraint 2 performs flow balancing between supplier-manufacturer and manufacturer-distribution center arcs. Constraint 3 ensures that flow of finished product from manufacturing center to distribution center cannot exceed the production capacity of manufacturing center. Constraint 4 performsflow balancing between manufacturing center-distribution center and distribution center-end-user arcs. Constraint 5 ensures that flow of finished product from distribution center to end-user cannot exceed the holding capacity of distribution center. Constraints 6 and 7 represent the demand satisfaction conditions. Constraints 8 and 9 restricts the maximum number of open facilities (MCs and DCs). Constraints 10 and 11 are the social sustainability conditions. Constraint 12 limits the maximum carbon emission allowed for an organization. And condition 13 represents the binary and non-negativity restrictions on the decision variables.

Collectively, these constraints create a comprehensive framework that optimizes supply chain operations while maintaining a balance between operational efficiency, customer satisfaction, social responsibility, and environmental consciousness.

Uncertainty modeling in the proposed model

In the proposed optimization model, various parameters have been assumed to be uncertain. The uncertain parameters involved in the given model are: capacity of different facilities viz. suppliers, manufacturing centers and distribution centers and the demand of end-users. This study utilizes chance constrained programming method to handle uncertainty.

3.10. *Chance constrained programming*

Chance-constrained programming (CCP) is a powerful and innovative optimization technique that addresses decision-making under uncertainty. This technique was first introduced by Charnes and Cooper (1959) to model the uncertain behavior of parameters involved in a linear programming problem. By considering uncertain parameters as random variables, CCP seeks to find solutions that satisfy constraints with a certain probability level. This approach finds diverse applications in various fields. Dong et al. (2014) applied CCP model to find the total cost at a specific risk stage, providing a basis for risk-cost trade off for watershed nutrient load reduction. Simic (2016) represented an interval-parameter CCP model for the management of few EOL products and Xie et al. (2011) provided a simulation based inexact CCP model. We first present below an application of CCP on a general linear programming problem.

Let us consider a stochastic linear programming problem:

$$F(x) = c^T x = \sum_{j\in J} c_j x_j \tag{14}$$

s.t

$$\sum_{j\in J} a_{ij} x_j = b_i \quad \forall i \in I \tag{15}$$

$$x_j \geqslant 0 \quad \forall j \in J \tag{16}$$

Here, c_j, a_{ij} and b_i are the random variables that follow normal distribution.

By using CCP in stochastic linear programming problem suggested by Nazemi and Tahmasbi (2013), Eq. 14–16 can be rewritten as:

$$F(x) = c^T x = \sum_{j\in J} c_j x_j \tag{17}$$

s.t

$$\Pr[\sum_{j\in J} a_{ij} x_j = b_i] \geqslant p_i \quad \forall i \in I \tag{18}$$

$$x_j \geqslant 0 \quad \forall j \in J \tag{19}$$

where, p_i represents respective probability for the constraint to be satisfied. Constraint 18 indicates that probability of meeting constraint 15 is at least p_i, where $0 \leqslant p_i \leqslant 1$. For simplicity, let us assume that the decision variables x_j's are deterministic.

Now for the constraint of the type:

$$\sum_{j\in J} a_{ij} X_i \leqslant b_i \quad \forall i \in I \qquad *$$

when only b_i's are the random variables. Let us assume that the random variable b_i follows normal distribution with mean u_i and the variance $Var(bi) = \Theta_i^2$.

$$b_i \sim N(u_i, Var(b_i)) \sim N(u_i, \Theta_i^2)$$

Now the constraint 18 can be restated as:-

$\Rightarrow$

$$\Pr[\sum_{j\in J} a_{ij} X_i \leqslant b_i] = \Pr[(\sum_{j\in J} a_{ij} X_i - u_i) \Big/ (\Theta_i) \leqslant (b_i - u_i) \Big/ (\Theta_i)] \quad \forall i \in I$$

$\Rightarrow$

$$\Pr[(\sum_{j\in J} a_{ij} X_i - u_i) \Big/ (\Theta_i) \leqslant (b_i - u_i) \Big/ (\Theta_i)] \geqslant p_i \quad \forall i \in I \tag{20}$$

Where $(b_i - u_i)/(\Theta_i)$, $\forall i \in I$ is a standard normal variate with mean 0 and variance 1. The above inequality can be rewritten as

$\Rightarrow$

$$\Pr[z \leqslant (\sum_{j\in J} a_{ij} X_i - u_i) \Big/ (\Theta_i)] \leqslant (1 - p_i) \quad \forall i \in I$$

If E_i represents the value of standard normal variate at which

$$\phi(E_i) = 1 - p_i < 0.5$$

Then the above constraint can be stated as

$\Rightarrow$

$$\phi[(\sum_{j\in J} a_{ij} X_i - u_i) \Big/ (\Theta_i)] \leqslant \phi(E_i) \quad \forall i \in I$$

This inequality is satisfied only if

$\Rightarrow$

$$(\sum_{j\in J} a_{ij} X_i - u_i) \Big/ (\Theta_i) \leqslant (E_i) \quad \forall i \in I$$

where, the standard normal variate

$$E_i = \phi^{-1}(1 - p_i) \tag{21}$$

$\Rightarrow$

$$\sum_{j\in J} a_{ij} X_i - u_i - E_i \Theta_i \leqslant 0 \quad \forall i \in I$$

$\Rightarrow$

$$\sum_{j\in J} a_{ij} X_i \leqslant u_i + E_i \Theta_i \quad \forall i \in I \qquad **$$

Thus the stochastic linear programming stated as Eq. 14–16 is equivalent to the deterministic optimization model stated as

$$F(x) = c^T x = \sum_{j\in J} c_j x_j \tag{22}$$

s.t

$$\sum_{j\in J} a_{ij} X_i \leqslant u_i + E_i \Theta_i \quad \forall i \in I \tag{23}$$

$$x_j \geqslant 0 \quad \forall j \in J \tag{24}$$

3.11. *Transformed model (After applying CCP)*

In the optimization model presented in subsection 3.9, constraints 1, 3, 5, 6 and 7 contain uncertain parameters. The uncertainty is there due to uncertain capacity at various locations and uncertain demand of the end-users. By using CCP, these constraints can be transformed as given below:

$$Constraint1 \rightarrow \Pr[\sum_{j\in J} Xsm_{ij} \leqslant S_i] \geqslant \gamma_i \quad \forall i \in I] \tag{25}$$

$$Constraint3 \rightarrow \Pr[\sum_{k\in K} Xmd_{jk} \leqslant P_j \alpha_j^m] \geqslant \delta_j \quad \forall j \in J \tag{26}$$

$$Constraint5 \rightarrow \Pr[\sum_{l\in L} Xde_{kl} \leqslant W_k \beta_k^d] \geqslant \eta_k \quad \forall w \in W \tag{27}$$

$$Constraint6 \rightarrow \Pr[\sum_{k\in K} Xde_{kl} \geqslant D_l] \geqslant \mu_l \quad \forall l \in L \tag{28}$$

$$Constraint7 \rightarrow \Pr[\sum_{l\in L} D_l = D^{total}] \geqslant \mu_l \tag{29}$$

Here, $\gamma_i, \delta_j, \eta_k$ and μ_l represent acceptable probabilities for respective constraint to be satisfied.

3.12. Reformulation.

The modified formulation of proposed optimization model after removing the uncertainty is given below:

Objective: Minimize Total Cost (Z) $= Z_1 + \pi Z_2 =$

$$\sum_{j\in J} F_j^m \alpha_j^m + \sum_{k\in K} F_k^d \beta_k^d + \sum_{i\in I}\sum_{j\in J} VC_{ij}^a Xsm_{ij} + \sum_{j\in J}\sum_{k\in K} VC_{jk}^b Xmd_{jk} + \sum_{k\in K}\sum_{l\in L} VC_{kl}^c Xde_{kl}$$

$$+ \pi\left(\sum_{j\in J} E_j^m \alpha_j^m + \sum_{k\in K} E_k^d \beta_k^d + \sum_{i\in I}\sum_{j\in J} VE_{ij}^a Xsm_{ij} + \sum_{j\in J}\sum_{k\in K} VE_{jk}^b Xmd_{jk} + \sum_{k\in K}\sum_{l\in L} VE_{kl}^c Xde_{kl}\right)$$

Subject to

$$\sum_{j\in J} Xsm_{ij} \leqslant mean\left(S_i\right) + \phi^{-1}\left(1-\gamma_i\right)\Theta_i \quad \forall i \in I \tag{30}$$

The constraint in stochastic Eq. 1 has been converted to deterministic Eq. 30. In Eq. 30, variables mean(S_i), $\forall j \in J$, represent average of different capacities for supplier $i \in I$. $\phi^{-1}(1-\gamma_i)$ represents the inverse of cumulative standard normal distribution of the random variable that follows normal distribution. Variables Θ_i's represent the standard deviation of capacities of different suppliers. The constraint 30 ensures that the flow of material from a supplier to different manufacturing centers does not exceed the transformed capacity of supplier, i.e.. $mean(S_i) + \phi^{-1}(1-\gamma_i)\,\Theta_i$. The supplying capacity of supplier can also be modified by changing the probabilities, i.e. γ_i's.

$$\sum_{i\in I} Xsm_{ij} = \sum_{k\in K} Xmd_{jk} \quad \forall j \in J \tag{31}$$

$$\sum_{k\in K} Xmd_{jk} \leqslant \left(mean\left(P_j\right) + \phi^{-1}\left(1-\delta_j\right)\Theta_j\right)\alpha_j^m \quad \forall j \in J \tag{32}$$

The constraint in stochastic Eq. 3 can be converted to deterministic Eq. 32. In Eq. 32, the variables mean(P_j), $\forall j \in J$, represent average production capacities of various manufacturing centers. $\phi^{-1}(1-\delta_j)$ represents the inverse of cumulative standard normal distribution of the random variable that follows normal distribution. Variables Θ_j's represent the standard deviation of production capacities of different manufacturing centers. The constraint 32 ensures that the flow of the product from a manufacturing center to different distribution centers does not exceed the transformed production capacity of manufacturing center, i.e.. $(mean(P_j) + \phi^{-1}(1-\delta_j)\,\Theta_j)$. The manufacturing center capacity can also be modified by changing the probabilities, i.e.. δ_j's.

$$\sum_{j\in J} Xmd_{jk} = \sum_{l\in L} Xde_{kl} \quad \forall k \in K \tag{33}$$

$$\sum_{l\in L} Xde_{kl} \leqslant \left(mean\left(W_k\right) + \phi^{-1}\left(1-\eta_k\right)\Theta_k\right)\beta_k^d \quad \forall k \in K \tag{34}$$

The constraint in stochastic Eq. 5 can be converted to deterministic Eq. 34. In Eq. 34, variables mean (W_k), $\forall k \in K$, represent average capacities of various distribution centers. $\phi^{-1}(1-\eta_k)$ represents the inverse of cumulative standard normal distribution of the random variable that follows normal distribution. Variables Θ_k's represent the standard deviation of capacities of different distribution centers. The constraint 34 ensures that the flow of the product from a distribution center to different end-users must not exceed the transformed capacity of the distribution center, i.e.. $(mean(W_k) + \phi^{-1}(1-\eta_k)\,\Theta_k)$. The distribution center capacity can also be modified by changing the probabilities, i.e. η_k's.

$$\sum_{k\in K} Xde_{kl} \geqslant mean\left(D_l\right) - \phi^{-1}\left(1-\mu_l\right)\Theta_l \quad \forall l \in L \tag{35}$$

The constraint in stochastic Eq. 6 can be converted to deterministic Eq. 35. In Eq. 35, the variables mean(D_l), $\forall l \in L$, represent average demands of different end-users. $\phi^{-1}(1-\mu_l)$ represents the inverse of cumulative standard normal distribution of the random variable that follows normal distribution. Variables Θ_l's represent the standard deviation of demands of different end-users. The constraint 35 ensures that the flow of the product from a distribution center to different end-users must be more than the transformed demand of end-users, i.e.. $mean(D_l) - \phi^{-1}(1-\mu_l)\,\Theta_l$. The demand of end-users can also be modified by changing the probabilities, i.e.. μ_l's.

$$\sum_{l\in L} mean\left(D_l\right) - \phi^{-1}\left(1-\mu_l\right)\Theta_l = D^{total} \tag{36}$$

The constraint in stochastic Eq. 7 can be converted to deterministic Eq. 36. The constraint 36 computes the total modified demand of the end-users. In Eq. 36, the variables mean(D_l), $\forall l \in L$, represent average demands of different end-users. $\phi^{-1}(1-\mu_l)$ represents the inverse of cumulative standard normal distribution of the random variable that follows normal distribution. Variables Θ_l's represent the standard deviation of demands of different end-users.

$$\sum_{j\in J} \alpha_j \leqslant M \tag{37}$$

$$\sum_{k\in K} \beta_k \leqslant N \tag{38}$$

$$\sum_{i\in I} (S_i^T \sum_{j\in J} Xsm_{ij}) \leqslant Time^{Max} \tag{39}$$

$$\sum_{l\in L} (Ac_l^e \sum_{k\in K} Xde_{kl}) \leqslant Ac^{max} D^{Total} \tag{40}$$

$$\sum_{j\in J} E_j^m \alpha_j^m + \sum_{k\in K} E_k^d \beta_k^d + \sum_{i\in I}\sum_{j\in J} VE_{ij}^a Xsm_{ij} + \sum_{j\in J}\sum_{k\in K} VE_{jk}^b Xmd_{jk} + \sum_{k\in K}\sum_{l\in L} VE_{kl}^c Xde_{kl} \leqslant C^{total} \tag{41}$$

$$\alpha_j^m, \beta_k^k = \{0,1\}; \quad Xsm_{ij}, Xmd_{jk}, Xde_{kl} \geqslant 0 \tag{42}$$

4. Numerical Illustration

The suggested model's utility is demonstrated by using a numerical example. The goal of this study is to create a strategic supply chain network that makes it easier to distribute products to end-users in different places in a way that is both cost effective and environmentally responsible. There are four levels in the proposed supply chain: supplier, manufacturing centers, distribution centers, and end-users.

To evaluate the performance and robustness of the proposed uncertain SCND, a series of numerical experiments were conducted using LINGO 19.0 software. One of the experiments focused on systematically varying the number of open facilities within the supply chain network. The objective of these experiments was to examine the impact of variations in available facilities on both total cost and carbon emissions, thus shedding light on the trade-offs between economic and environmental sustainability objectives.

Table 2 provides the result of the experiment of varying the number of open facilities. As shown in Table 2, influence of increment in number of facilities (manufacturing centers and distribution centers) was observed on total cost and carbon emissions. Initially, total cost and carbon emmision values reduce with increase in number of facililities. Later, as number of facilities increases beyond case 3, the total cost and carbon emission also increase in accordance with the complex interactions of production, transportation, and establishment costs. The optimal solution was achieved in case 3 when 12 manufacturing centers and 12 distribution centers remain operational and corresponding total cost is 26004710 while the carbon emission is 251419 tons.

Sensitivity Analysis

4.1. *Variation in the number of open facilities*

Supply chain network design is a complex optimization process that involves strategic decisions regarding the configuration of facilities to achieve cost efficiency and sustainability goals. The two graphs presented in Figs. 3 and 4 provide an insightful analysis of the impact of altering the number of open facilities within the proposed uncertain SCND model. Specifically, these graphs show the interplay between facility availability and total cost, shedding light on critical considerations for supply chain decision-makers.

In Fig. 3, the x-axis represents the number of open manufacturing centers, while the y-axis depicts the corresponding total cost. The number of distribution centers was fixed at 12 for this experiment. With a fixed number of distribution centers, this graph offers a clear perspective on how variation in the number of open manufacturing centers influence overall cost. As the number of open MCs increases, the total cost demonstrates specific trends. At lower values of open MCs, total costs is relatively higher due to under utilization of capacity and higher operational costs per unit produced. As the number of open MCs rises, economies of scale can be leveraged, potentially leading to a decline in total cost. However, beyond a certain point, the total cost starts increasing due to over utilization of open facilities and increase in transportation cost between the facilities.

Table 2
Variation in the number of facilities.

Cases	No. of Manufacturing center open	No. of Distribution center open	Total cost	Carbon emission (in tons)
1	11	11	27112460	262194
2	11	12	26505360	256269
3	12	12	26004710	251419
4	13	13	26024530	251512
5	14	14	26049850	251682
6	15	15	26079350	251872
7	16	16	26110750	252062
8	16	17	26132750	252145
9	17	18	26171170	252390
10	20	20	26304340	253330

Similarly, Fig. 4 examines the influence of changing the number of open distribution centers while maintaining a constant number of manufacturing centers. Number of manufacturing centers was fixed at 12 for this experiment. This graph provides insights into the intricate relationship between number of open distribution centers and total cost within the supply chain.

When number of open DCs is low, total costs is comparatively higher due to higher transportation expenses and reduced responsiveness to demand fluctuations. As the number of open DCs increases, transportation costs might decrease and distribution-related costs could rise. The optimal point on this graph represents a balance where the benefits of increased distribution efficiency counteract the additional costs associated with maintaining more open DCs.

4.2. *Variation in the supplier capacity constraint probability γ_i*

Effective supply chain management involves navigating uncertainties, and the probability of supplier capacity constraints plays a pivotal role in determining the robustness of the system. The two graphs presented in this subsection, Figs. 5 and 6, provide insights into how variations in supplier capacity constraints probabilities influence both the total cost and total emission within the proposed uncertain SCND model.

In Fig. 5, the x-axis represents the probability of supplier capacity constraints γ_i, while the y-axis illustrates the corresponding total cost. Fig. 5 demonstrates specific trend in the relationship between the probability of supplier capacity constraints and the resulting total cost. Initially, at lower levels of probability (0.72), the total cost is observed to be relatively high. The probabilities below the chosen range, such as 0.72, lead to infeasible solutions within the system. As the probability of supplier capacity constraints increases to a certain critical point, a notable decrease in total cost has been observed. This decline reflects the positive impact in the supply chain strategy and efficient resource allocation. However, beyond this point, a reversal occurs, and the total cost starts increasing as the probability of the supplier capacity constraint increases.

The insights captured from Fig. 6 states the link between the probability of supplier capacity constraints and the subsequent total emission. The x-axis denotes the probability of supplier capacity constraints, and the y-axis represents the corresponding total emission. This graph highlights the intricate dynamics between supply chain disruptions and environmental aspect of sustainability. This graph demonstrates a consistent upward trend wherein the total emissions increase with a rise in the probability of constraints. The upward trend in total emissions with an increase in probability of supplier capacity constraints is attributed to a combination of interconnected factors. The inverse relationship between the probability and the capacity of the supplier plays a crucial role. As the probability rises, it signifies a decrease in supplier capacity and vice versa.

When the probability of supplier capacity constraints increases, a decline in supplier capacity indicates that there is a possible demand for additional suppliers to meet manufacturing requirements. Emissions resulting from manufacturing and transportation activities increase as a result.

The observed dynamics of total cost and emission concerning varying supplier capacity constraint probabilities emphasize the importance of proactive supply chain management strategies. By identifying the critical inflection point in Fig. 5, managers can make informed decisions to strike a balance between cost-saving measures and resilience actions. Additionally, Fig. 6 emphasizes the need to prioritize sustainability efforts. Collectively, these insights support the formulation of strategic decisions that balance operational efficiency, supply chain resilience, and environmental sustainability.

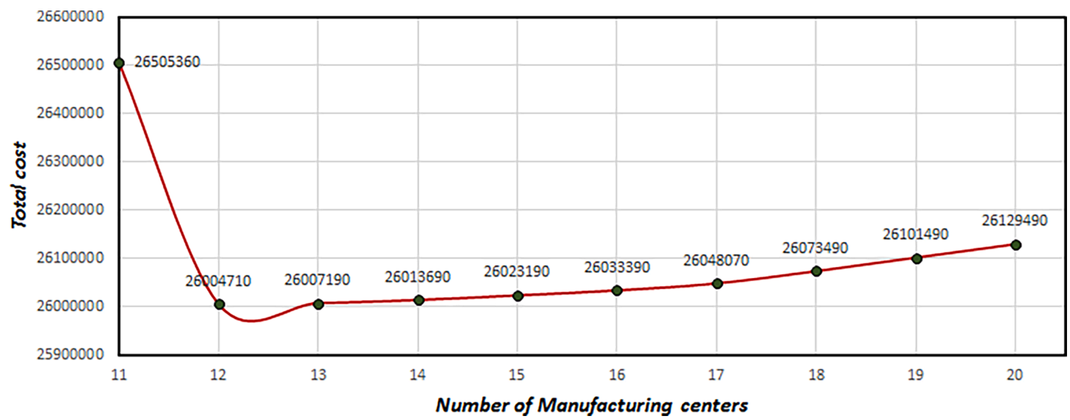

Fig. 3. Variation in the number of Manufacturing centers.

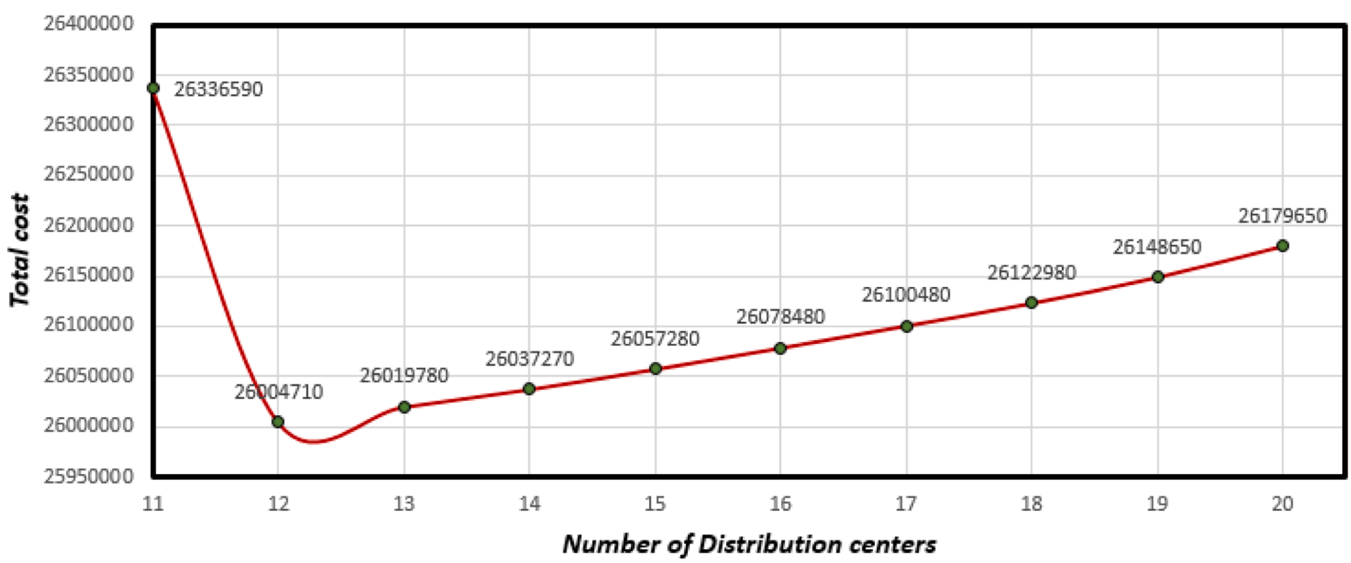

Fig. 4. Variation in the number of Distribution centers.

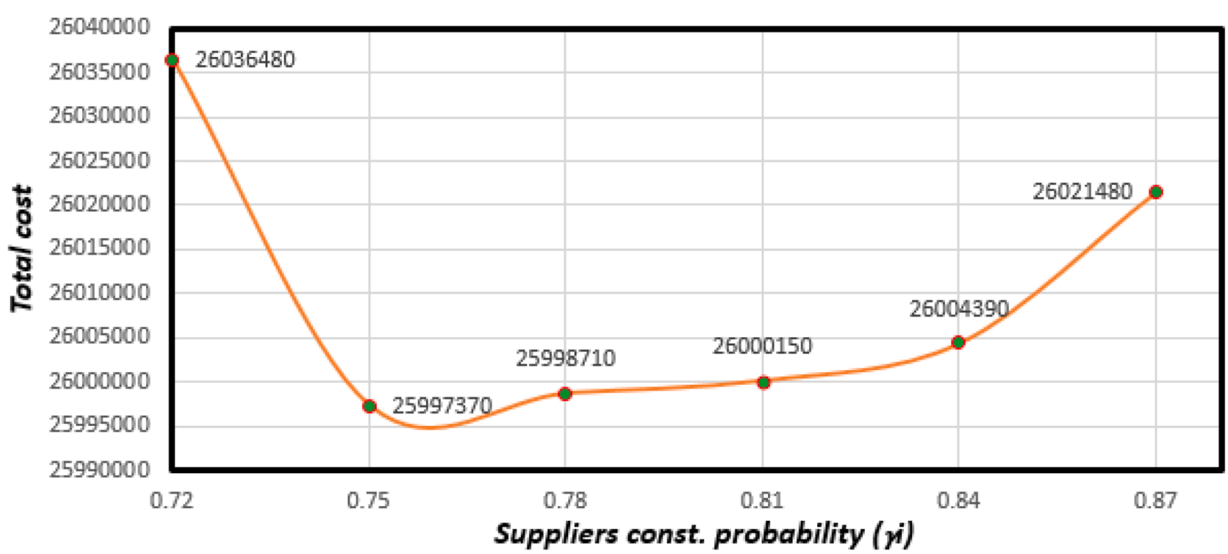

Fig. 5. Total cost Vs change in γ_i.

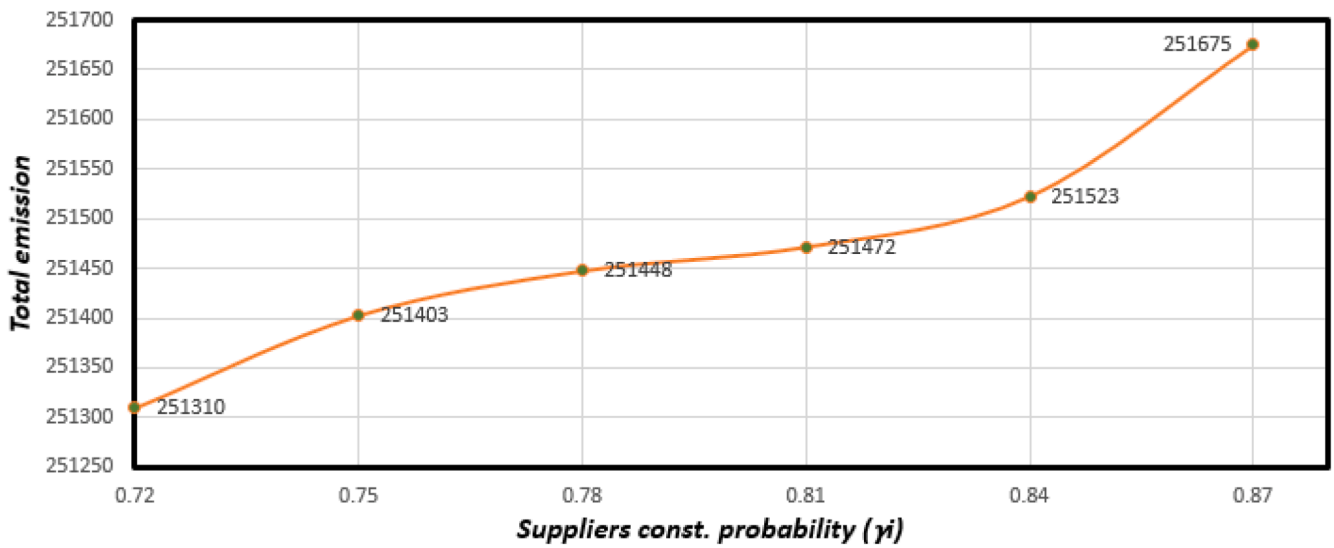

Fig. 6. Total emission Vs change in γ_i.

4.3. Variation in the manufacturing center capacity constraint probability δ_j

In this subsection, we investigate the impact of varying manufacturing center capacity constraints probability within the proposed uncertain SCND model. The subsequent graphs, Figs. 7 and 8, mirror the trends previously observed in Figs. 5 and 6. These graphs reveal how changes in manufacturing center capacity constraint probabilities influence both operational costs and environmental considerations within the supply chain.

Fig. 7 shows an interesting trend in the relationship between manufacturing center capacity constraint probabilities and the resulting total cost. Initially, as the probability of manufacturing center capacity constraints is set to be 0.75, it shows that the resulting total cost is too high. The probabilities below the chosen range, such as 0.75, lead to infeasible solutions and including these infeasible regions on the x-axis would not provide meaningful insights. This outcome reflects the potential cost implications associated with operational disruptions, where constrained manufacturing capacity leads to increased production expenses. However, at a certain threshold probability, the graph indicates a decline in total cost. This decline signifies the beneficial impact of robust manufacturing capacity, enhancing production capabilities and reducing operational costs. Beyond this threshold, further increase in the probability of manufacturing center capacity constraints contribute to a subsequent rise in total cost due to operational inefficiencies and additional costs incurred.

Fig. 8 shows parallel trend established in Fig. 6, showcasing the relationship between manufacturing center capacity constraint probabilities and total emission. As the probability of manufacturing center capacity constraints increases, the total emission demonstrate a consistent upward trajectory. Disruptions adding from manufacturing center capacity constraints can lead to sub-optimal decisions and resource allocation, resulting in increasing emissions. This relationship emphasizes the need to manage manufacturing center capacity constraints proactively to mitigate the environmental consequences of disruptions.

These graphs provide further depth to the analysis by extending the examination to manufacturing center capacity constraints. By recognizing the critical threshold in Fig. 7, decision-makers can strategically optimize manufacturing center capacity to achieve a balance between

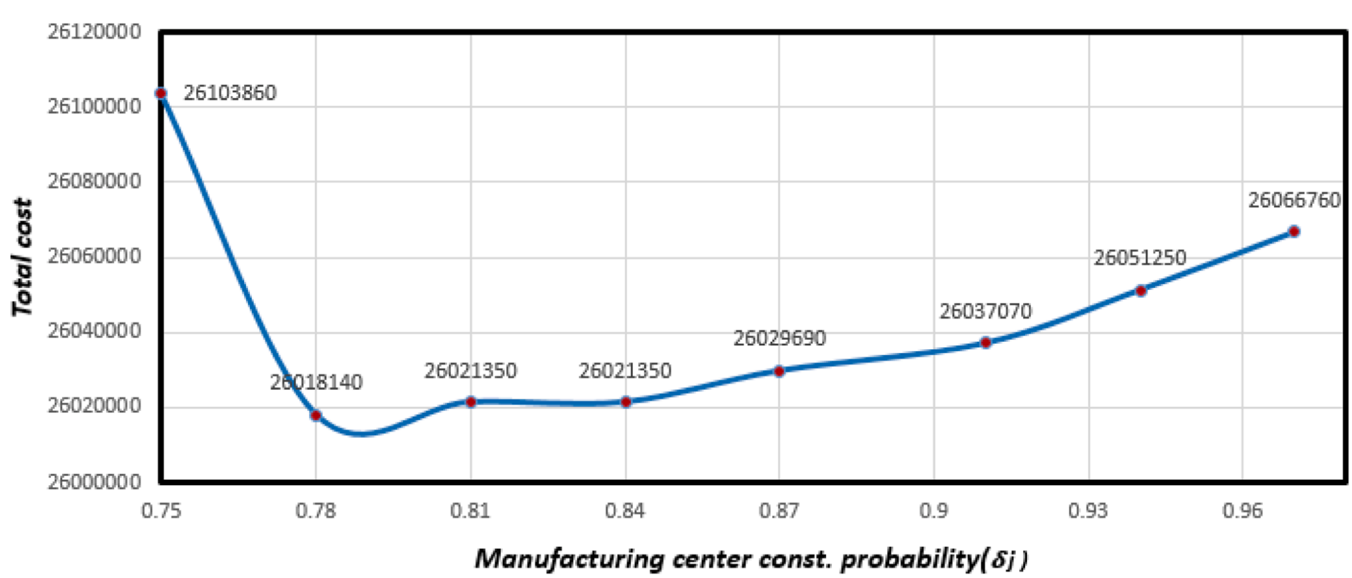

Fig. 7. Total cost Vs change in δ_j.

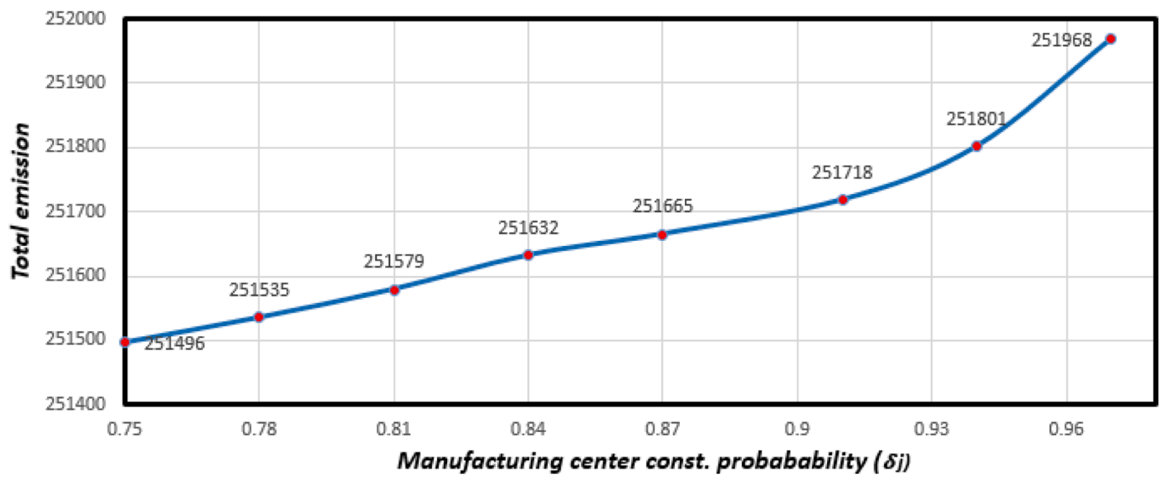

Fig. 8. Total emission Vs change in δ_j.

cost efficiency and operational stability. Additionally, Fig. 8 emphasizes the need to prioritize sustainability efforts to offset emissions growth resulting from disruptions.

4.4. Variation in the distribution center capacity constraint probability η_k

Extending the examination of supply chain constraints, the analysis further explores the effects of distribution center capacity constraints on total cost and total emissions within the context of the proposed uncertain SCND model. The subsequent graphs, Figs. 9 and 10, reflect the observed relationships between the variation in the probability of DC capacity constraints and supply chain total cost/total emission, further emphasizing the intricate dynamics between supply chain economic considerations, and environmental impact.

Fig. 9 offers valuable insights into the relationship between distribution center capacity constraint probabilities and the resulting total cost. As the probability of distribution center capacity constraints increases, a corresponding upward trajectory in total cost becomes evident. This pattern underscores the potential cost implications arising from operational disruptions related to constrained distribution center capacities. The graph's trend highlights the importance of proactive measures to manage distribution center capacity constraints and maintain operational efficiency. For the probability below 0.75, the system becomes infeasible and therefore these values have not been represented in Fig. 9 as including these infeasible areas on the x-axis would not provide any meaningful information.

Fig. 10 shows the trend which revealing the connection between distribution center capacity constraints probabilities and total emission. As the probability of distribution center capacity constraints rises, total emissions exhibit a consistent increase. Disruptions caused by constraints in distribution center capacities can prompt sub optimal decisions in terms of transportation and resource allocation. Consequently, emissions escalate due to expedited shipping, inefficient distribution, and associated carbon-intensive activities. For the probabilities below 0.75, the system becomes infeasible and therefore these values have not been represented in Fig. 10 as including these infeasible areas on the x-axis would not provide any meaningful information.

Collectively, these insights empower supply chain professionals to make informed decisions that combine economic efficiency, operational stability, and environmental responsibility in the face of distribution center capacity uncertainties.

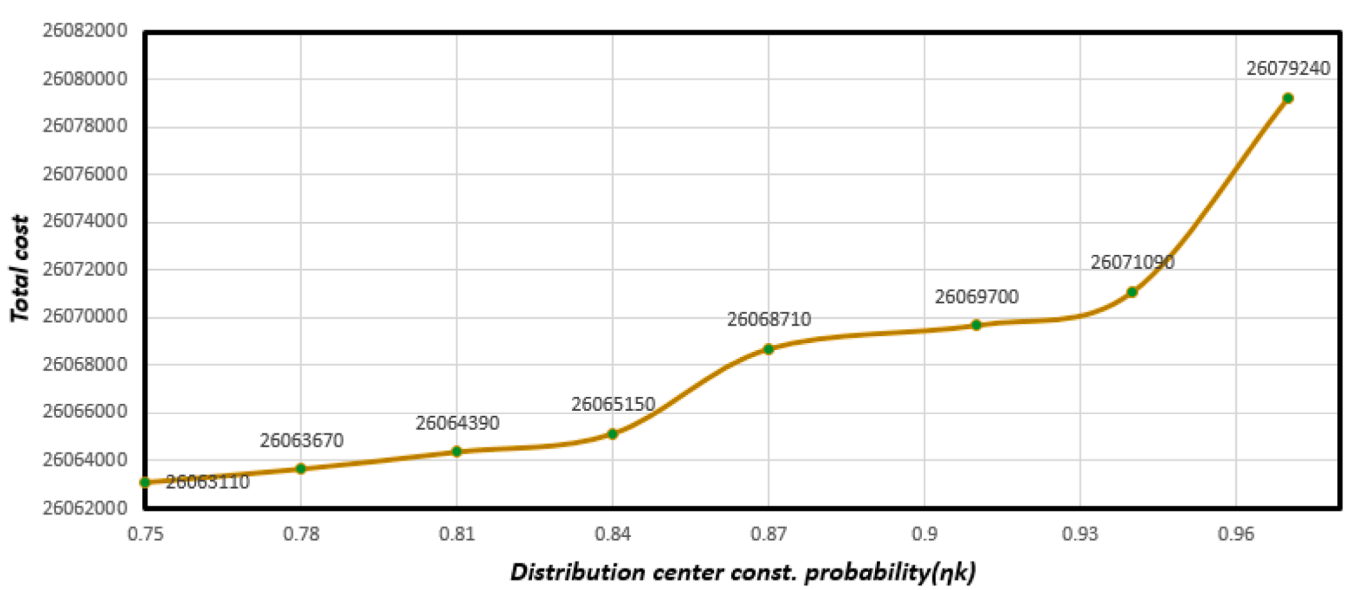

Fig. 9. Total cost Vs change in η_k.

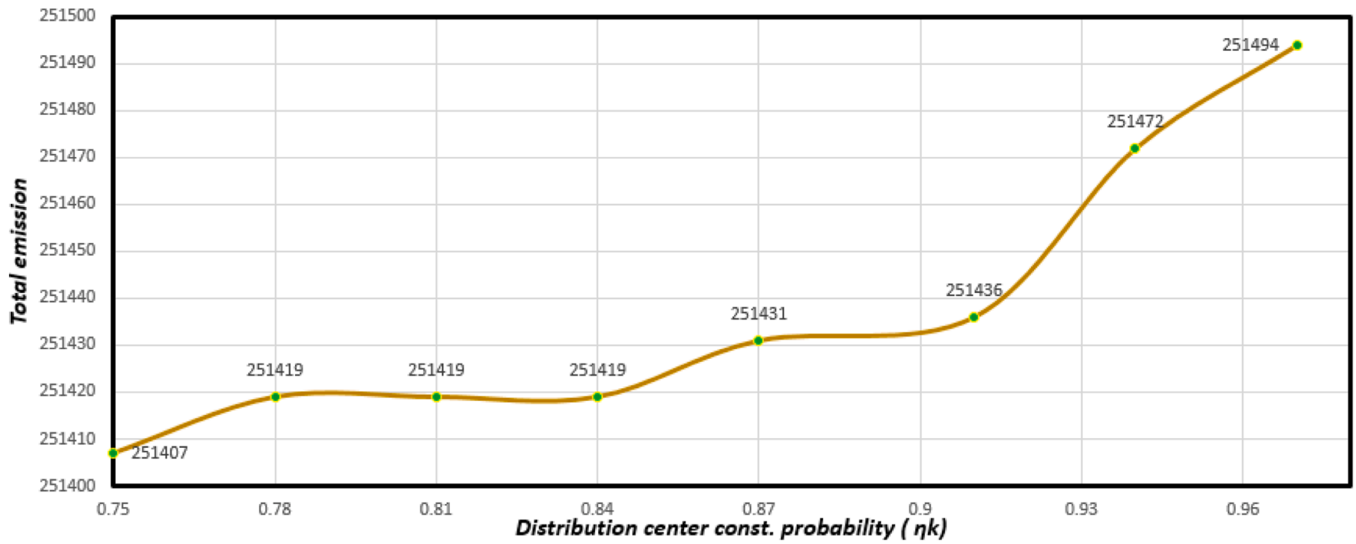

Fig. 10. Total emission Vs change in η_k.

4.5. Variation in the demand constraint probability μ_l

In this subsection, we analysis the impact of demand satisfaction constraints probability to search the implications of these constraints on total cost and total emissions within the framework of the proposed uncertain SCND model. The ensuing graphs, Figs. 11 and 12, provide a distinctive perspective, revealing how the interplay between demand satisfaction and supply chain dynamics impacts both financial considerations and environmental outcomes.

Fig. 11 shows a valuable trend between the demand satisfaction constraint probabilities and the resulting total cost. The graph portrays a declining trend. Initially, as the probability of demand satisfaction constraints is set to 0.75, the total cost value is on a higher side that reflects the financial implications of increasing demand fulfillment and there are infeasible solutions for probabilities below the selected range, and including these infeasible regions on the x-axis would not provide useful information. As the demand satisfaction constraint probability increases, the total cost shows a decreasing trend throughout the graph. This decline underscores the impact of comprehensive demand satisfaction strategies, including enhanced demand forecasting, and responsive production.

Parallel to the trend established in Fig. 11, Fig. 12 illustrates the relationship between demand satisfaction constraint probabilities and total emissions. So, the graph shows a relationship between demand fulfillment and environmental responsibility. As the probability of demand satisfaction constraints rises, total emissions follow a declining trend. This decline underscores the potential environmental benefits of proactive demand satisfaction measures that enhance supply chain responsiveness and optimize transportation.

The graphical insights presented in this subsection underscore the criticality of effective demand satisfaction strategies in supply chain management. Collectively, these insights empower supply chain practitioners to formulate strategies that holistically align operational efficiency, demand satisfaction, and environmental sustainability.

4.6. Variation in the total carbon emission cap

This subsection explores the intricate relationship between total cost

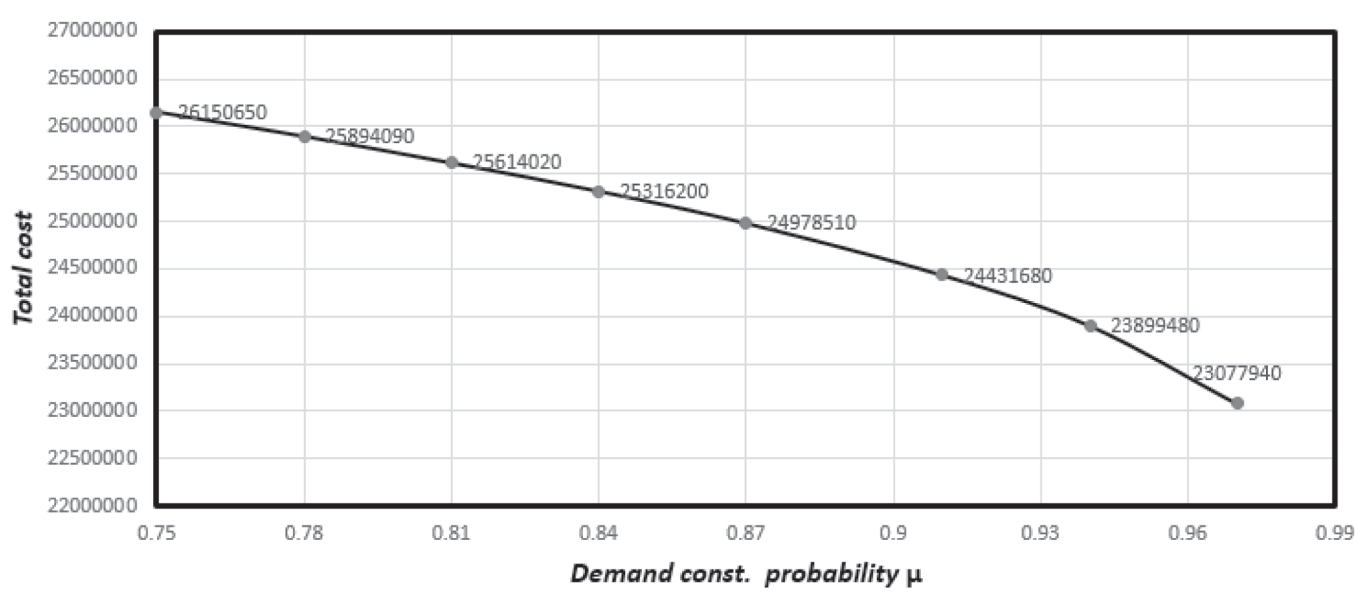

Fig. 11. Total cost Vs change in μ_l.

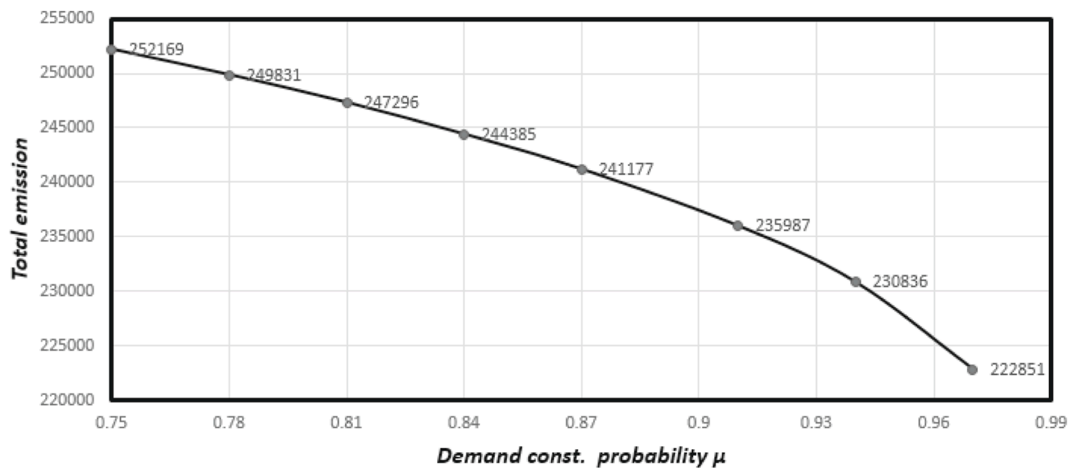

Fig. 12. Total emission Vs change in μ_l.

and environmental impact. The influence of variations in carbon emissions on total cost has been studied within the context of the proposed uncertain SCND model. The ensuing graph provides a visual narrative that shows the dynamic trade-offs between economic efficiency and environmental sustainability.

Fig. 13 offers a compelling visualization of the interaction between total cost and the carbon emission cap. The x-axis denotes varying levels of the carbon emission cap, while the y-axis portrays the corresponding total cost. The graph reveals a linear trend, where total cost exhibits an incremental rise with increase in carbon emission.

This linear relationship underscores the inherent trade-offs between cost considerations and environmental commitments. The graph's linear progression symbolizes the financial impact of adopting sustainable practices, where reducing emissions often entails investments in cleaner technologies, optimized transportation, and improved resource utilization.

5. Greedy Based Heuristic

A greedy-based algorithm is a heuristic approach used in solving optimization problems where the aim is to find the best solution from a set of choices. The term "greedy" refers to the strategy of making locally optimal choices at each step with the hope that these choices will lead to a global optimal solution. In other words, the algorithm focuses on immediate gains without considering the long-term consequences of those choices.

The central idea behind a greedy algorithm is to iteratively select the best option available at each stage, making decisions that seem the most advantageous at the moment. This can be advantageous for solving problems with large solution spaces, as it simplifies the decision-making process and reduces computational complexity. However, the trade-off is that greedy algorithms might not always lead to the absolute best solution, as they do not account for potential future trade-offs or variations in the problem.

In the context of optimization problems, strength of a greedy-based algorithm lies in its simplicity and efficiency. It often works well for problems where locally optimal choices contribute significantly to the global optimum. However, it might not be suitable for problems with intricate dependencies or those requiring an exhaustive exploration of all possibilities.

Heuristic algorithms are commonly employed in various fields, including computer science, operations research, and engineering, to solve problems such as scheduling, network optimization, and resource allocation. Yavari and Geraeli (2019) developed an efficient heuristic algorithm, YAG, to solve the large size problem of MILP robust optimization model for green closed-loop SCND of perishable goods. By hybridizing two meta-heuristic algorithms, AICA and VNS, Devika et al. (2014) developed a novel algorithm named as HIV to improve the solution efficiency for a CLSC with multiple goals. While heuristic algorithms do not necessarily find the optimal solution in all cases, a well-designed greedy algorithm can provide satisfactory results and serve as a useful tool in decision-making processes.

To address the intricate challenges of our sustainable supply chain model, a greedy algorithm was strategically employed. This algorithm

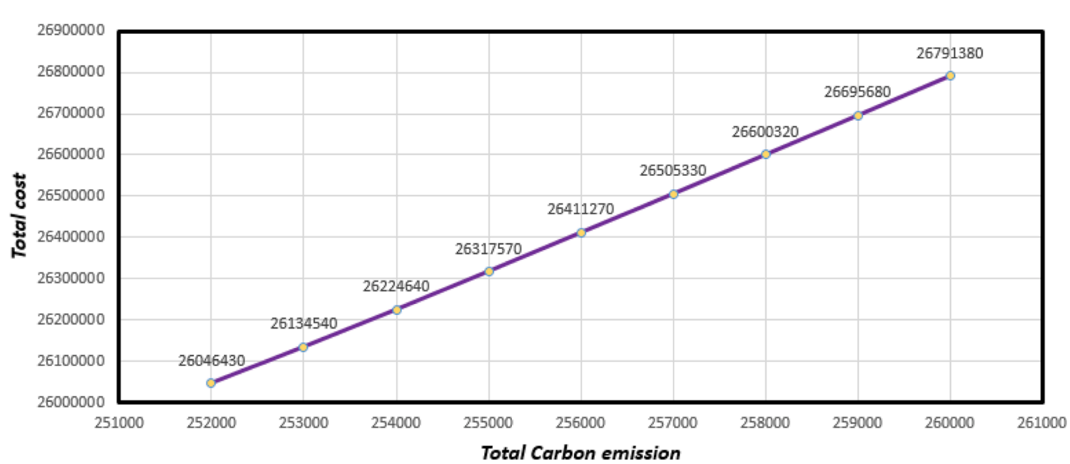

Fig. 13. Total cost Vs change in total CO_2 emission cap.

serves as the backbone of our decision-making process, effectively navigating the complex interplay between suppliers, manufacturing centers, distribution centers, and end-users. At each step, the algorithm makes locally optimal choices, selecting the most advantageous options based on immediate gains. This approach enables us to efficiently manage operational costs and carbon emissions throughout the supply chain. Leveraging the algorithm's simplicity and computational efficiency, we optimized the product flow between supplier to manufacturing center, manufacturing center to distribution center, and distribution center to end-users while considering capacity constraints and customer demands. Furthermore, the algorithm also considers the restrictions on the maximum number of open manufacturing and distribution centers, ensuring a balance between facility utilization and the broader sustainability objectives. By iteratively refining the facility allocations and transportation routes, the algorithm empowers us to achieve a solution that aligns with our overarching goals of minimizing costs and environmental impact. Through the strategic application of the greedy algorithm, we achieve a pragmatic and effective way of addressing the complexities inherent in our sustainable supply chain model to achieve a harmonious balance between economic efficiency and ecological responsibility.

The primary objective of the employed greedy-based algorithm was to quickly and efficiently optimize decision-making processes within our sustainable supply chain model. By focusing on locally optimal choices at each juncture, the algorithm aimed to achieve a balance between time-saving and cost-efficiency. The algorithm's immediate decision-making approach allowed us to swiftly navigate the complex network of suppliers, manufacturing centers, distribution centers, and end-users, efficiently allocating resources and minimizing the time required to determine optimal/near-optimal solutions. By prioritizing immediate gains, the algorithm contributed to reduced computational complexity, offering a pragmatic way to address complex optimization challenges without exhaustive exploration of all possibilities. Ultimately, the objective of the greedy-based algorithm aligned with the broader aim of achieving resource efficiency, cost minimization, and timely decision-making in the context of our sustainable supply chain model.

Working of the algorithm.

The algorithm operates by iteratively optimizing the flow of products through a four-stage supply chain, encompassing suppliers, manufacturing centers, distribution centers, and end-users. Employing a greedy approach, the algorithm strategically allocates product flows at each step to minimize total costs, including fixed operating cost and transportation cost, and carbon emissions associated with facility operations and transportation.

As shown in Fig. 14, the algorithm begins by initializing parameters, data, variables and defining the objective function that captures cost and emission considerations. Through a series of iterations known as the 'Greedy Loop Approach' the algorithm navigates through distinct stages. At each stage, it selects flow allocations that locally minimize the combined cost and emission factors. This loop is repeated to iteratively refine the flow allocations. The algorithm incorporates checks for constraints like capacity restriction and demand satisfaction. Importantly, it employs termination conditions to ensure an efficient trade-off between computational time and solution quality. Once the flow allocations are optimized, the algorithm incorporates maximum open facilities restrictions to check the robustness of the algorithm. Then algorithm proceeds to solution validation, where the results are analysed for feasibility and effectiveness. The algorithm concludes by presenting a solution that enhances decision-making in supply chain management.

To evaluate the effectiveness and efficiency of the proposed algorithm, a comparative analysis was conducted against the established optimization software, LINGO 19. Table 3 presents a trade-off comparison of the results obtained from both approaches in terms of total cost, time taken, and the corresponding cost and time gaps.

The outcomes of this comparative assessment reveal interesting insights on the performance of the algorithm. As shown in Fig. 15, our algorithm shows an advantage in terms of computational time, demonstrating an approximate 80% reduction in processing duration compared to LINGO 19 software. This accelerated performance is a valuable asset, particularly in real-time decision-making scenarios where quick insights are imperative for responsive supply chain management.

However, it's important to note that this efficiency gain comes with a cost implication. As shown in Fig. 16, the results indicate an approximate 18% cost increase when utilizing the heuristic algorithm against LINGO 19 software. This cost gap underscores the intricate balance between computational time and solution value. The heuristic algorithm, while providing accelerated results, may encounter certain scenarios where total cost is higher and therefore optimization-related compromises have to be made.

Table 4 present a comparison of the optimization model and the greedy algorithm at larger instances by varying the number of nodes. As shown in Table 4, the greedy algorithm has been found to be time-efficient in comparison to the optimization model across larger instances that demonstrates its scalability. For example in case 11, the runtime of the optimization model in LINGO 19 was approximately equal to 7 hours. Whereas, the greedy algorithm could find a solution to the same case (case 11) in around 32 minutes. This shows the time-efficiency of the proposed greedy based algorithm for handling larger and more complex instances.

In the broader context of supply chain management, this comparison serves as a strategic guideline for decision-makers. While the heuristic algorithm significantly enhances computational efficiency, the trade-off between cost and time should be carefully considered based on the urgency of decision requirements and the acceptable margin of cost deviation. This analysis underscores the heuristic algorithm's potential as a valuable tool in supply chain decision-making.

Algorithm

A step-by-step working of the proposed algorithm can be found below:

Step-1: Let iteration count p equal to 0; the initial iteration.

S^0= Set of all suppliers with capacity $Cap_i^{S^0}$; M^0= Set of all manufacturing centers with capacity $Cap_j^{M^0}$; D^0= Set of all distribution centers with capacity $Cap_k^{D^0}$; E^0= Set of all end-users with demand $Dem_l^{E^0}$. For each $i \in S^0$ and $j \in M^0$, set $X_{ij} = 0$; for each $j \in M^0$ and $k \in D^0$, set $X_{jk} = 0$; for each $k \in D^0$ and $l \in E^0$, set $X_{kl} = 0$; and for each $l \in E^0$; $Dem_l^{E^0} = 0$.

Step-2: For $p = p + 1$; the intermediate iterations.

For each $i \in S^0$; compute $\sum_{j \in M_0} X_{ij} \leqslant Cap_i^{S^0}$. Further, for the cost per unit flow from supplier $i \in S^0$ to MC $j \in M^0$ such that $Cost_{sm} = VC_{ij} + \pi VE_{ij}$; choose X_{ij} that minimizes $Cost_{sm}$ and identify $j \in M^0$ satisfying $\sum_{i \in S^0} X_{ij} = \sum_{k \in D^0} X_{jk}$, go to *Step* −3.

Step-3:

For the location of manufacturing center $j \in M^0$; check the capacity restriction if the MC is established there, i.e.. identifying α_j to compute $\sum_{k \in D^0} X_{jk} \leqslant Cap_j^{M^0} \alpha_j$. Further, for the cost per unit flow from MC $j \in M^0$ to DC $k \in D^0$ such that $Cost_{md} = VC_{jk} + \pi VE_{jk}$; choose X_{jk} that minimizes $Cost_{md}$ and identify $k \in D^0$ satisfying $\sum_{j \in M^0} X_{jk} = \sum_{l \in E^0} X_{kl}$, go to *Step* −4.

Step-4:

For the distribution center location $k \in D^0$; check the capacity constraint if the DC is established there, i.e.. identifying β_k to compute $\sum_{l \in E^0} X_{kl} \leqslant Cap_k^{D^0} \beta_k$. Further, for the cost per unit flow from DC $k \in D^0$ to end-user $l \in E^0$ such that $Cost_{de} = VC_{kl} + \pi VE_{kl}$; choose X_{kl} that minimize $Cost_{de}$, go to *Step* −5.

Step-5:

For the each demand location $l \in E^0$, Step-4 identifies all $k \in D^0$ which is open. Now, for every $k \in D^0$ which is open; identify $l \in E^0$ (or X_{kl}) satisfying $\sum_{k \in D^0} X_{kl} \geqslant Dem_l^{E^0}$, go to *Step* −6.

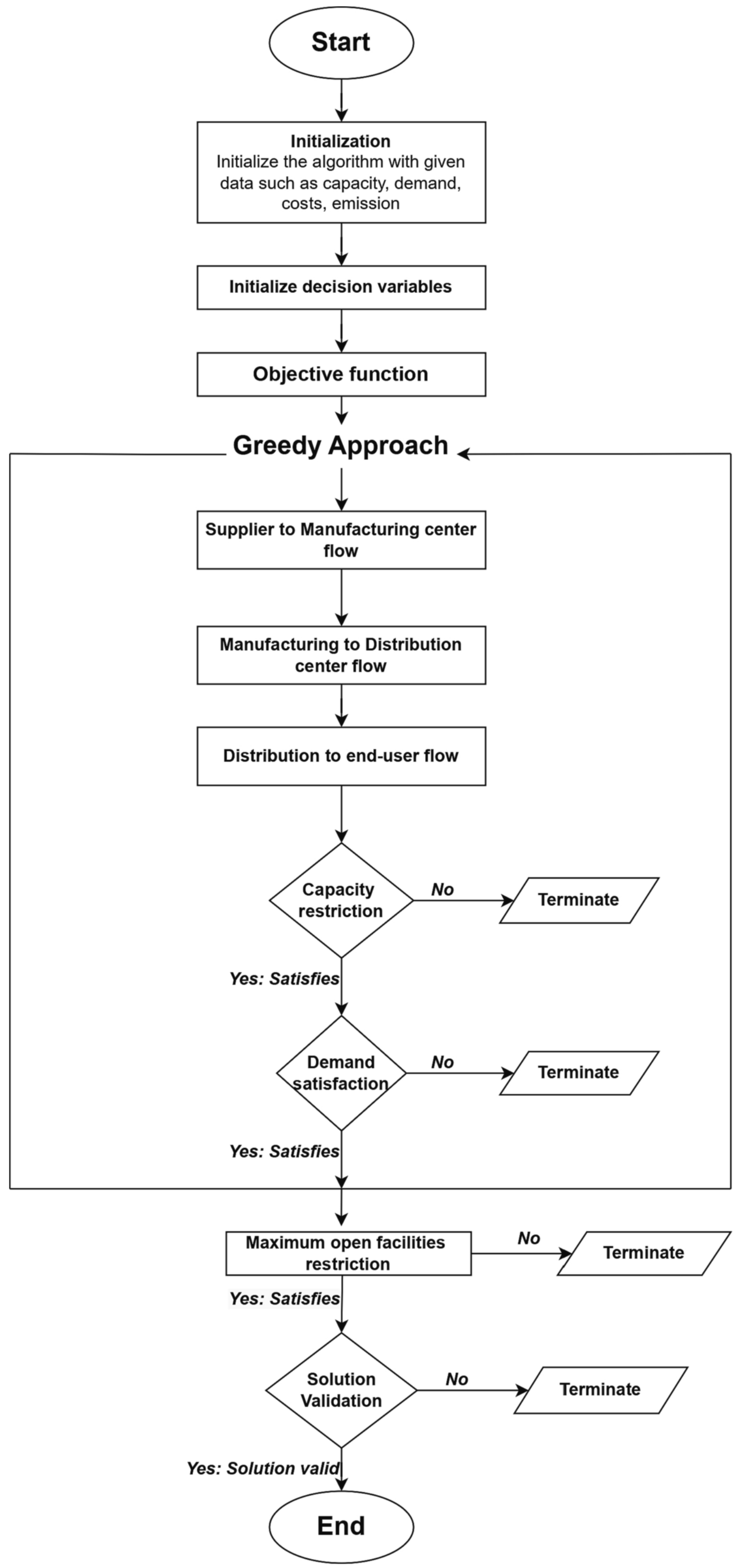

Fig. 14. Flowchart of the Greedy-based heuristic solution approach of the model.

Table 3
Comparison of results between LINGO 19.0 software and heuristic.

Cases	No. of Manufacturing center open	No. of Distribution center open	LINGO 19 software Solution		Heuristic solution		Deviation from optimality (%)	Time gap (%)
			Total cost	Time (in sec)	Total cost	Time (in sec)		
1	11	11	27112460	7.68	32508180	1.04	19.90	86.45
2	11	12	26505360	9.57	31690900	3.04	19.56	68.23
3	12	12	26004710	10.63	30795600	2.22	18.42	79.11
4	13	13	26024530	6.37	30754150	1.17	18.17	81.63
5	14	14	26049850	4.64	30726070	0.86	17.95	81.46
6	15	15	26079350	4.77	30717220	0.5	17.78	89.51
7	16	16	26110750	2.62	30715690	0.34	17.63	87.02
8	16	17	26132750	2.09	30715620	0.26	17.53	87.56
9	17	18	26171170	0.37	30715690	0.2	17.36	45.95
10	20	20	26304340	0.22	30715690	0.19	16.77	13.63

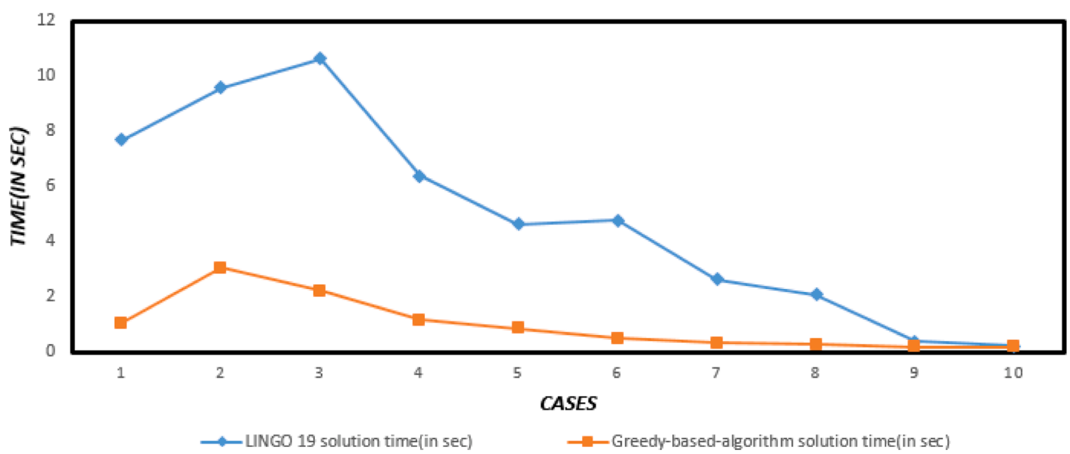

Fig. 15. Time gap comparison.

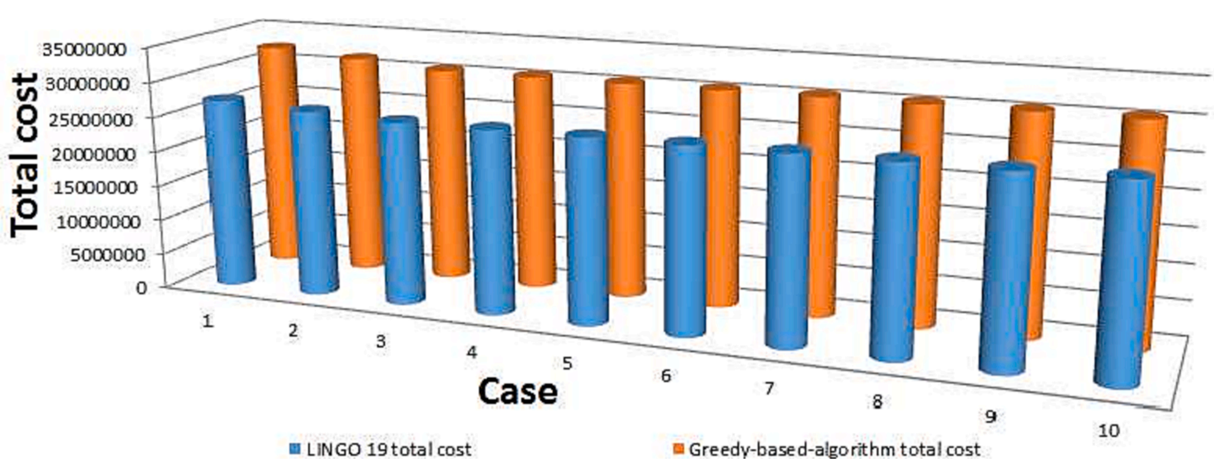

Fig. 16. Total cost gap comparison.

Step-6:

If conditions established above are satisfied, $\forall\ i \in S^0; j \in M^0; k \in D^0; l \in E^0$; then stop; otherwise go to *Step* −2.

6. Discussion

The findings of this research align with the increasing emphasis on sustainability in supply chain management. Stricter government regulations have pushed companies to recognize the importance of addressing environmental and social concerns along with economic considerations. By integrating sustainability into supply chain practices, organizations can foster long-term success, enhance brand reputation, and contribute positively to society and the environment.

This research paper identifies a research gap in the existing literature concerning the limited consideration of all three dimensions of sustainability in supply chain management. By presenting a model that takes into account economic, environmental, and some social factors, this study fills a crucial void in the field, offering a more comprehensive and holistic approach to sustainable supply chain design.

The proposed model represents a substantial step-forward in the

Table 4
Performance of the optimization model and greedy based heuristic at larger instances.

Cases	Number of Nodes				LINGO 19 software Solution		Heuristic solution		Deviation from optimality(%)	Time gap(%)
	Supplier(i)	MC(j)	DC(k)	End-user(k)	Total cost	Time (in sec)	Total cost	Time (in sec)		
1	10	20	20	30	26004710	10.63	30795600	2.22	18.42	79.05
2	11	22	22	33	28822780	11.2	35363741	2.87	22.69	74.37
3	12	24	24	36	31462730	28.5	39622014	7.3	25.93	74.38
4	13	26	26	39	34071290	35.32	43142861	10.07	26.62	71.47
5	14	28	28	42	36876360	75.4	49696124	19.05	34.76	74.73
6	15	30	30	45	39484930	124.28	54142041	29.7	37.12	76.08
7	16	32	32	48	41966320	250.1	57372533	44.21	36.71	82.32
8	17	34	34	51	44396190	342.8	62662889	57.2	41.14	83.31
9	18	36	36	54	46754950	621.75	65878012	72.06	40.90	88.40
10	19	38	38	57	49428530	5166.3	68722626	493.21	39.03	90.45
11	20	40	40	60	51937224	25843.5	69224271	1937.36	33.28	92.27

pursuit of sustainable supply chains. By leveraging CCP, the research effectively addresses uncertainties that are inherent in supply chain decision-making. With the incorporation of CCP, decision-makers gain the ability to assess and manage these risks by enhancing the resilience and adaptability of the supply chain.

The integration of multiple objectives of reducing supply chain costs including establishment, production, and transportation costs, and minimizing greenhouse gas emissions, emphasizes the model's commitment to economic and environmental sustainability. This multi-objective optimization approach finds a trade-off between economic and environmental sustainability dimensions, providing decision-makers with valuable insights for making informed choices aligned with their sustainability goals.

Sensitivity analysis conducted in this study has provided invaluable insights into the model's robustness and flexibility. Decision-makers can explore the impact of various parameters, such as the carbon footprint cap, the number of facilities, and probabilities, on the overall cost and the emissions within the supply chain. This analysis empowers them to make well-informed decisions, considering uncertainties that might arise in dynamic business environments.

The utilization of a heuristic to solve the proposed model demonstrates the computational intelligence of the research. By employing both an exact solution method and a heuristic approach, the study showcases the model's capabilities in efficiently addressing supply chain complexities and finding near-optimal solutions for large-scale networks.

The implications of this research are significant for supply chain managers, policy-makers, and other stakeholders. By embracing this model, organizations may create supply chains that not only meet regulatory requirements but also contribute positively to society and the environment.

The optimization model employed in this study is based on mixed integer linear programming with uncertainties. The proposed model focuses on cost minimization, and the current framework primarily addresses economic, environmental, and selected social factors within the SCND. Additionally, social parameters are assumed to be deterministic in this study, limiting the precision of social sustainability estimation. Consideration of uncertain social parameters could offer a more accurate reflection in the model.

While this study has introduced a pioneering approach to integrating sustainability dimensions into uncertain supply chain network design, there are several directions for further exploration. One direction is the integration of additional uncertain parameters in the objective function and constraints. By extending the proposed optimization framework to encompass a wider range of uncertain variables such as fluctuating market demands, variable transportation costs, and uncertain supplier capabilities, a more resilient and adaptable supply chain design can be formulated. Incorporating these additional uncertainties will move the model more closer to reality and it will help in making decisions that not only optimize economic, environmental, and social considerations but also pro-actively address the unpredictable nature of real-world supply chain operations. This approach will require advanced techniques such as robust optimization or stochastic programming to effectively manage the intricacies of uncertain parameters.

In conclusion, this research advances the understanding and implementation of sustainability in supply chain management by proposing an innovative model that incorporates economic, environmental, and limited social dimensions. With a focus on addressing uncertainties, optimizing flow levels, and conducting sensitivity analysis, the model provides valuable decision support for businesses to build resilient, sustainable, and responsible supply chain networks.

7. Conclusion

This research paper sheds light on the critical aspect of sustainability in supply chain management. Driven by stricter government regulations addressing environmental pollution and social injustice, businesses are increasingly recognizing the need to integrate sustainability principles into their supply chain practices. This study makes a significant contribution by proposing an MILP model for designing an uncertain supply chain network that aims to minimize overall costs while incorporating carbon emissions and social factors of suppliers training and customer complaints. This research addresses uncertainty through the utilization of CCP and perform sensitivity analysis to explore the impact of various parameters. This research also presents a greedy based heuristic for solving larger instances of the problem in an efficient manner.

While this study generates valuable insights by the integration of economic, environmental, and social sustainability dimensions within supply chain management through the proposed uncertain SCND model, there are certain limitations and future directions that should also be acknowledged:

- The optimization model considered in this study is a mixed integer linear programming model with uncertainties. However, the model can be extended to a formulation where parameters and variables are non-linear.
- The proposed optimization model focuses on a single period, single product problem. By extending it to a multi-product, multi-period problem, a more robust and adaptive supply chain network design may evolve that addresses diverse challenges faced by industries.
- The proposed optimization model is a cost minimizing optimization model. Inclusion of social objectives may enhance the practicality of proposed work.
- The model primarily focuses on economic, environmental (carbon emissions), and selected social factors within the SCND. Other important aspects of social sustainability, such as labor practices, ethical sourcing, and community engagement, are not captured within the current framework.
- The social parameters considered in this study are assumed to be deterministic. A more precise estimation of social sustainability can

be made by considering uncertain social parameters in the given model.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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