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Optimizing Supply Chain Network Design under Uncertainty: A Practical Methodology for Sustainable Value Creation

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Abstract

Evaluating supply chain network (SCN) designs is critical for organizations striving to optimize operations and achieve sustainable value creation. However, conventional models often oversimplify, failing to account for the complexities inherent in real-world supply chain environments. In this study, we propose an advanced approach to SCN evaluation that strikes a balance between practicality and sophistication, leveraging real-world data to inform decision-making. Our methodology aims to bridge the gap between theoretical models and practical implementation, offering a pathway to sustainable value creation in SCN design. By incorporating risk analysis, resilience modeling, and solution methods tailored to uncertainty, our approach provides a comprehensive framework for addressing the challenges of SCN design under uncertainty. Simulation results validate the efficacy of our methodology in facilitating informed decision-making and strategic planning within organizations.

Keywords: *Supply chain network, evaluation, uncertainty, resilience modeling, decision-making, strategic planning, sustainable value creation.*

Introduction

Supply chain networks (SCNs) constitute the backbone of contemporary economies, serving as intricate webs through which goods and services flow from suppliers to end consumers. The efficient functioning of SCNs is paramount for businesses to maintain competitiveness, enhance operational efficiency, and meet evolving consumer demands. Consequently, the evaluation and optimization of SCNs have emerged as critical tasks for organizations seeking to navigate the complexities of modern markets effectively.

Traditionally, approaches to SCN evaluation have predominantly focused on factors such as cost minimization, operational efficiency, and service quality. While these metrics are undeniably important, they often fail to capture the full spectrum of challenges and uncertainties inherent in today's business landscape. Factors such as supply chain disruptions, market volatility, sustainability concerns, and geopolitical risks introduce layers of complexity that necessitate a more comprehensive and nuanced approach to SCN evaluation.

In response to these challenges, our research endeavors to present an enhanced methodology for evaluating SCNs that goes beyond traditional metrics and incorporates a broader range of considerations. At the heart of our approach lies the integration of resilience modeling, strategic planning, and sustainable value creation principles into the SCN evaluation framework. By doing so, we aim to equip decision-makers with the tools and insights necessary to navigate uncertainty, build resilience, and drive sustainable value creation within their supply chain operations.

Through a combination of theoretical frameworks, empirical analysis, and practical implementation, our research seeks to bridge the gap between academic theory and industry practice in supply chain management. By offering a holistic and adaptive methodology that can accommodate diverse SCN contexts, we aspire to contribute to the advancement of supply chain management theory and the development of innovative strategies for building resilient and sustainable supply chains in today's dynamic business environment (Jamil et al., 2023).

Literature Review

The literature review delves into various crucial subjects within the expansive domain of supply chain management, each offering unique insights and methodologies aimed at enhancing operational efficiency, sustainability, and value creation. Central to this exploration is the optimization of supply chain network design under conditions of uncertainty, a topic of increasing significance in contemporary scholarship.

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Scholars advocate for the integration of uncertainty considerations into design models to better align with sustainability goals. Notably, methodologies such as stochastic programming and scenario analysis are highlighted for their potential to bolster resilience in supply chain operations amidst uncertainty. Jahani et al. (2024) contribute to this discourse by conducting a comprehensive review of supply chain network design (SCND) models, with a specific focus on their financial dimensions. Their analysis underscores the importance of incorporating financial perspectives into SCND models, thereby enriching decision-making processes, and advancing sustainable value creation initiatives. Building upon this foundation, Ala et al. (2024) propose a novel fuzzy multi-objective optimization model tailored for sustainable healthcare supply chain network design. This model, integrating advanced optimization techniques like the multi-objective gray wolf optimizer (MOGWO) and non-dominated sorting genetic algorithm II (NSGA-II), aims to minimize total costs and environmental impacts while maximizing social factors such as job creation. Gao et al. (2024) extend the discourse by presenting a robust optimization framework specifically designed for the design of a dual-channel closed-loop supply chain network. Their research addresses the challenges faced by industries, particularly in transitioning to more environmentally sustainable supply chains, by considering uncertain demand and carbon cap-and-trade policies. This framework integrates multiple transport modes and policy considerations to optimize supply chain network design, ultimately contributing to the creation of sustainable and environmentally friendly supply chain networks. Additionally, Varma et al. (2024) delve into the evolving trajectory of research in Supply Chain Flexibility (SCF), shedding light on its development and themes through citation path analysis. Their study identifies promising avenues for future research, particularly in exploring the intersection of Industry 4.0 and SCF, aligning with the broader aim of understanding the role of flexibility in supply chain decision-making processes. Furthermore, Belhadi et al. (2024) investigate the utilization of digital capabilities in managing uncertainties within the African agri-food supply chain, emphasizing the role of digital technologies in enhancing supply chain resilience. This study provides valuable insights into managing supply chain uncertainty in vulnerable regions, highlighting the practical implications for managers in developing suitable strategies during geopolitical disruptions. Chen et al. (2024) contribute to the discourse by examining decision-making within supply chains considering yield uncertainty and corporate social responsibility (CSR) under different market power structures. Their analysis reveals the complex interplay between various factors in shaping optimal decisions, underscoring the need for nuanced approaches to address uncertainty and CSR concerns. Additionally, Tang (2006) and Snyder et al. (2016) provide comprehensive reviews of risk management in supply chain network design and facility location decisions under uncertainty, respectively. These studies offer valuable insights into managing risks and uncertainties within supply chains, emphasizing the importance of incorporating uncertainty considerations into decision-making processes to foster resilience and sustainability. Furthermore, Ganguly et al. (2018) discuss the critical role of resilience in managing supply chain disruptions, highlighting strategies for building resilience and providing insightful examples across various industries. Finally, Chopra and Meindl (2007), Christopher (2016), Christopher and Holweg (2011), and Ivanov and Sokolov (2013) contribute to the discourse by exploring strategic dimensions, logistics, and management facets of supply chains, each underscoring the importance of agility, flexibility, and resilience in navigating turbulent business environments and fostering sustainable value creation. Collectively, these studies offer a comprehensive understanding of supply chain dynamics and decision-making processes, encompassing optimization, risk management, strategic planning, and system-theoretic approaches, all aimed at enhancing sustainability and value creation within supply chains.

Developed Supply Chain Design Model

A robust and efficient supply chain is the cornerstone of success for any organization, necessitating strategic decisions in logistics, production allocation, and distribution network management. Anticipating future challenges and optimizing supply chain operations are essential for maximizing profitability and maintaining competitiveness. In this context, supply chain network (SCN) design emerges as a pivotal tool for strategic decision-making, enabling companies to align their resources with market demands and operational objectives.

The objective of SCN design is to optimize the configuration and operations of the supply chain network to maximize discounted expected profits. This involves a multi-dimensional approach, considering factors such as production capacity, distribution channels, inventory management, and market responsiveness. To formulate the SCN design problem, we adopt the following notation:

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$t \in T$: Periods in the planning horizon

$h \in H$: Reengineering cycles in the planning horizon

$t \in T_h$: Periods in the reengineering cycle h

$h(t)$: Reengineering cycle of period t

α : A discount rate, based on the weighted average costs of capital of the company.

$\boldsymbol{X}_t$: The level of each network's activity in period $t \in T$.

$\boldsymbol{F}_t$: Flow of the product in period $t \in T$.

$\boldsymbol{I}_t$: Level of strategic inventory of the product in period $t \in T$.

$\boldsymbol{U}_t$: Penalty paid to the vendor under contract if the minimum sales value specified in the contract isn't reached in period $t \in T$.

$\boldsymbol{Y}_h$: Binary variable equal to 1 if, opening, using, or closing a platform at the beginning of planning cycle $h \in H$.

$\boldsymbol{W}_h$: Binary variable equal to 1 if a market-policy is selected during cycle $h \in H$.

$\boldsymbol{Z}_h$: Binary variable equal to 1 if a transportation capacity is selected at the beginning of cycle $h \in H$.

$\boldsymbol{V}_h$: Binary variable equal to 1 if a vendor is selected at the beginning of cycle $h \in H$

The deterministic mathematical formulation of the SCN design problem is presented as:

$$Max \sum_{t \in T} \frac{1}{(1+\alpha)^t} \left[A_t \boldsymbol{F}_t - B_t\left(\boldsymbol{F}_t, \boldsymbol{X}_t, \boldsymbol{I}_t, \boldsymbol{U}_t, \boldsymbol{Y}_{h(t)}, \boldsymbol{W}_{h(t)}, \boldsymbol{Z}_{h(t)}, \boldsymbol{V}_{h(t)}\right)\right] \quad (1)$$

$$s.t$$

$$C_t\left[\boldsymbol{W}_{h(t)}, \boldsymbol{Y}_{h(t)}\right] \leq b_t \quad \forall t \in T \quad (2)$$

$$G_t \boldsymbol{F}_t + P_t\left[\boldsymbol{W}_{h(t)}, \boldsymbol{Y}_{h(t)}, \boldsymbol{Z}_{h(t)}\right] \leq 0 \quad \forall t \in T \quad (3)$$

$$M_t[\boldsymbol{F}_t, \boldsymbol{U}_t, \boldsymbol{X}_t, \boldsymbol{I}_t] + O_t\left[\boldsymbol{Y}_{h(t)}, \boldsymbol{V}_{h(t)}\right] \leq 0 \quad \forall t \in T \quad (4)$$

$$L_t[\boldsymbol{X}_t, \boldsymbol{F}_t, \boldsymbol{I}_t] \leq d_t \quad \forall t \in T \quad (5)$$

$$\boldsymbol{X}_t, \boldsymbol{F}_t, \boldsymbol{I}_t, \boldsymbol{U}_t \geq 0 \quad \forall t \in T \quad (6)$$

$$\boldsymbol{Y}_{h(t)}, \boldsymbol{W}_{h(t)}, \boldsymbol{Z}_{h(t)}, \boldsymbol{V}_{h(t)} \in \{0,1\} \quad \forall t \in T \quad (7)$$

Where $(\mathbf{X}_t, \mathbf{F}_t, \mathbf{I}_t, \mathbf{U}_t)$ be the follower variables and $(\mathbf{Y}_{h(t)}, \mathbf{W}_{h(t)}, \mathbf{Z}_{h(t)}, \mathbf{V}_{h(t)})$ the design variables or the leader variables.$A_t$and $B_t$are two matrices denoting the revenues and expenditures associated to decision variables during the planning horizon.C_t,G_t,P_t,M_t,O_t, L_t are the matrices of parameters.b_t and d_t are two left side vectors.

Equation (2) presents the constraints related to the market policy and internal location configurations via the use of platform selection variables. Equation (3) presents the goals of the company in demand and penetration level in the market, the reception and shipping capacity limits and the network transportation capacity restrictions. Equation (4) presents limits of the supplied quantity by the vendor of each product and the benefit of the vendor's contract conditions. In addition to the constraints related to the throughput and inventory level for each platform. Equation (5) is about flow equilibrium constraints, inventory account constraints and inventory-throughput relationship constraints. Finally non-negativity and binary constraints are given.

In addressing uncertainty and dynamic market conditions, the deterministic program is extended to a multi-period two-stage stochastic program with recourse. This framework accommodates various scenarios and decision-making stages, allowing organizations to adapt their strategies based on evolving conditions.

In this challenge $(\boldsymbol{Y}_h, \boldsymbol{W}_h, \boldsymbol{Z}_h, \boldsymbol{V}_h)$ corresponds to the resource levels to be acquired, and ω corresponds to a specific scenario from the whole set of scenarios denoted by Ω.

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If the initial decisions are taken in the beginning of the planning horizon, these decisions are denoted by $D_1 = (\boldsymbol{Y}_1, \boldsymbol{W}_1, \boldsymbol{Z}_1, \boldsymbol{V}_1)$ describing the first cycle decisions and coupled by a given scenario ω.

In order to model the first order decisions variables as being dependent on the recourse variables, it is necessary to differ between the decisions that must be taken at the beginning of the planning horizon in the first cycle (h=1) noted as D_1 and $(\boldsymbol{Y}_{h(t)}, \boldsymbol{W}_{h(t)}, \boldsymbol{Z}_{h(t)}, \boldsymbol{V}_{h(t)})$ presenting the decisions taken in cycle h (h>1) of each periods of time $t \in T$. The former decisions variables are defined according to a specific scenario $\omega \in \Omega$ and they may change from one to another. These design variables are noted by $\left(\boldsymbol{Y}_{h(t)}(D_1,\omega), \boldsymbol{W}_{h(t)}(D_1,\omega), \boldsymbol{Z}_{h(t)}(D_1,\omega), \boldsymbol{V}_{h(t)}(D_1,\omega)\right)$ showing that the design decisions during the cycle periods depend on the first ones taken at the beginning of the planning horizon under a particular scenario. D_1 does not act in response to scenario ω and it is determined before any information regarding the uncertain data has been obtained.

$$Q(D_1,\omega) = Max \sum_{t\in T} \frac{1}{(1+\alpha)^t}\left[A_t(\omega)F_t(D_1,\omega)\right] - \sum_{h>1}\sum_{t\in T_h} \frac{1}{(1+\alpha)^t} B_{h(t)}(\omega) \begin{bmatrix} F_t(D_1,\omega), X_t(D_1,\omega), I_t(D_1,\omega), U_t(D_1,\omega) \\ , Y_{h(t)}(D_1,\omega), W_{h(t)}(D_1,\omega), Z_{h(t)}(D_1,\omega), V_{h(t)}(D_1,\omega) \end{bmatrix} \quad (8)$$

$s.t$

$$C(\omega)\left[\boldsymbol{W}_{h(t)}(D_1,\omega), \boldsymbol{Y}_{h(t)}(D_1,\omega)\right] \le b(\omega) \quad \forall t \in T \quad (9)$$

$$G(\omega)\boldsymbol{F}_t(D_1,\omega) + P(\omega)\left[\boldsymbol{W}_{h(t)}(D_1,\omega), \boldsymbol{Y}_{h(t)}(D_1,\omega), \boldsymbol{Z}_{h(t)}(D_1,\omega)\right] \le 0 \quad \forall t \in T \quad (10)$$

$$M(\omega)\left[\boldsymbol{F}_t(D_1,\omega), \boldsymbol{U}_t(D_1,\omega), \boldsymbol{X}_t(D_1,\omega), \boldsymbol{I}_t(D_1,\omega)\right] + O(\omega)\left[\boldsymbol{Y}_{h(t)}(D_1,\omega), \boldsymbol{V}_{h(t)}(D_1,\omega)\right] \le 0 \ \forall t \in T \quad (11)$$

$$L(\omega)\left[\boldsymbol{X}_t(D_1,\omega), \boldsymbol{F}_t(D_1,\omega), \boldsymbol{I}_t(D_1,\omega)\right] \le d(\omega) \quad \forall t \in T \quad (12)$$

$$\boldsymbol{X}_t(D_1,\omega), \boldsymbol{F}_t(D_1,\omega), \boldsymbol{I}_t(D_1,\omega), \boldsymbol{U}_t(D_1,\omega) \ge 0 \quad \forall t \in T \quad (13)$$

$$\boldsymbol{Y}_{h(t)}(D_1,\omega), \boldsymbol{W}_{h(t)}(D_1,\omega), \boldsymbol{Z}_{h(t)}(D_1,\omega), \boldsymbol{V}_{h(t)}(D_1,\omega) \in \{0,1\} \forall t \in T \quad (14)$$

To take under consideration this structure of this decision problem, the recourse version of the original program as follow:

$$Max \sum_{t\in T} \frac{1}{(1+\alpha)^t}\left[A_t(\omega)\boldsymbol{F}_t(D_1^j,\omega)\right] - \sum_{h>1}\sum_{t\in T_h} \frac{1}{(1+\alpha)^t} B_{h(t)}(\omega) \begin{bmatrix} \boldsymbol{F}_t(D_1^j,\omega), \boldsymbol{X}_t(D_1^j,\omega), \boldsymbol{I}_t(D_1^j,\omega), \boldsymbol{U}_t(D_1^j,\omega) \\ , \boldsymbol{Y}_{h(t)}(D_1^j,\omega), \boldsymbol{W}_{h(t)}(D_1^j,\omega), \boldsymbol{Z}_{h(t)}(D_1^j,\omega), \boldsymbol{V}_{h(t)}(D_1^j,\omega) \end{bmatrix} \quad (15)$$

$s.t$

$$C(\omega)\left[\boldsymbol{W}_{h(t)}(D_1^j,\omega), \boldsymbol{Y}_{h(t)}(D_1^j,\omega)\right] \le b(\omega) \quad \forall t \in T \quad (16)$$

$$G(\omega)\boldsymbol{F}_t(D_1^j,\omega) + P(\omega)\left[\boldsymbol{W}_{h(t)}(D_1^j,\omega), \boldsymbol{Y}_{h(t)}(D_1^j,\omega), \boldsymbol{Z}_{h(t)}(D_1^j,\omega)\right] \le 0 \quad \forall t \in T \quad (17)$$

$$M(\omega)\left[\boldsymbol{F}_t(D_1^j,\omega), \boldsymbol{U}_t(D_1^j,\omega), \boldsymbol{X}_t(D_1^j,\omega), \boldsymbol{I}_t(D_1^j,\omega)\right] + O(\omega)\left[\boldsymbol{Y}_{h(t)}(D_1^j,\omega), \boldsymbol{V}_{h(t)}(D_1^j,\omega)\right] \le 0 \quad \forall t \in T \quad (18)$$

$$L(\omega)\left[\boldsymbol{X}_t(D_1^j,\omega), \boldsymbol{F}_t(D_1^j,\omega), \boldsymbol{I}_t(D_1^j,\omega)\right] \le d(\omega) \quad \forall t \in T \quad (19)$$

$$\boldsymbol{X}_t(D_1^j,\omega), \boldsymbol{F}_t(D_1^j,\omega), \boldsymbol{I}_t(D_1^j,\omega), \boldsymbol{U}_t(D_1^j,\omega) \ge 0 \quad \forall t \in T \quad (20)$$

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$$\boldsymbol{Y}_{h(t)}(D_1^j,\omega),\boldsymbol{W}_{h(t)}(D_1^j,\omega),\boldsymbol{Z}_{h(t)}(D_1^j,\omega),\boldsymbol{V}_{h(t)}(D_1^j,\omega)\in\{0,1\}\quad\forall t\in T \tag{21}$$

It is necessary to specify that the matrixes of parameters and costs in both sides of the sub-problems depend also on the scenarios and may change from a scenario to another.

The resulting stochastic program (15)-(21) is resolved for every generated scenario $\omega \in \Omega$.

The comparison and the selection of solutions (designs) are performed by means of several performance measures defined next sections.

Design Evaluation Approach

This section outlines an evaluation approach for multi-objective design optimization, aimed at identifying optimal supply chain network (SCN) designs amidst uncertainty throughout the planning horizon. The primary objective at the design evaluation level is to select the most suitable SCN design from a finite set of options J where $J \geq 2$, including the existing status quo. This selection process is crucial for ensuring that the chosen design is robust and adaptive to potential disruptions in the future business environment.

Anticipating future challenges and disruptions is essential for enabling users and designers to proactively respond and adjust the SCN structure accordingly. Therefore, the design evaluation procedure is formulated based on a response optimization model, which considers the following components:

Decision Variables (D): Represents the design decisions associated with each SCN design option.

Objective Function (F): Seeks to optimize multiple objectives simultaneously, reflecting the diverse goals and priorities of the organization.

Constraints (C): Imposes limitations and requirements on the SCN design, ensuring feasibility and practicality.

Uncertainty Considerations (U): Accounts for the inherent uncertainty and variability in future business conditions, allowing for robust decision-making under uncertainty.

$$Max\sum_{t\in T}\frac{1}{(1+\alpha)^t}\left[A_t(\omega)\boldsymbol{F}_t(D_1^j,\omega)\right] - \sum_{h>1}\sum_{t\in T_h}\frac{1}{(1+\alpha)^t}B_{h(t)}(\omega)\begin{bmatrix}\boldsymbol{F}_t(D_1^j,\omega),\boldsymbol{X}_t(D_1^j,\omega),\boldsymbol{I}_t(D_1^j,\omega),\boldsymbol{U}_t(D_1^j,\omega)\\ ,\boldsymbol{Y}_{h(t)}(D_1^j,\omega),\boldsymbol{W}_{h(t)}(D_1^j,\omega),\boldsymbol{Z}_{h(t)}(D_1^j,\omega),\boldsymbol{V}_{h(t)}(D_1^j,\omega)\end{bmatrix} \tag{22}$$

$s.t$

$$C(\omega)\left[\boldsymbol{W}_{h(t)}(D_1^j,\omega),\boldsymbol{Y}_{h(t)}(D_1^j,\omega)\right]\leq b(\omega)\quad\forall t\in T \tag{23}$$

$$G(\omega)\boldsymbol{F}_t(D_1^j,\omega)+P(\omega)\left[\boldsymbol{W}_{h(t)}(D_1^j,\omega),\boldsymbol{Y}_{h(t)}(D_1^j,\omega),\boldsymbol{Z}_{h(t)}(D_1^j,\omega)\right]\leq 0\quad\forall t\in T \tag{24}$$

$$M(\omega)\left[\boldsymbol{F}_t(D_1^j,\omega),\boldsymbol{U}_t(D_1^j,\omega),\boldsymbol{X}_t(D_1^j,\omega),\boldsymbol{I}_t(D_1^j,\omega)\right]+O(\omega)\left[\boldsymbol{Y}_{h(t)}(D_1^j,\omega),\boldsymbol{V}_{h(t)}(D_1^j,\omega)\right]\leq 0\quad\forall t\in T \tag{25}$$

$$L(\omega)\left[\boldsymbol{X}_t(D_1^j,\omega),\boldsymbol{F}_t(D_1^j,\omega),\boldsymbol{I}_t(D_1^j,\omega)\right]\leq d(\omega)\quad\forall t\in T \tag{26}$$

$$\boldsymbol{X}_t(D_1^j,\omega),\boldsymbol{F}_t(D_1^j,\omega),\boldsymbol{I}_t(D_1^j,\omega),\boldsymbol{U}_t(D_1^j,\omega)\geq 0\quad\forall t\in T \tag{27}$$

$$\boldsymbol{Y}_{h(t)}(D_1^j,\omega),\boldsymbol{W}_{h(t)}(D_1^j,\omega),\boldsymbol{Z}_{h(t)}(D_1^j,\omega),\boldsymbol{V}_{h(t)}(D_1^j,\omega)\in\{0,1\}\quad\forall t\in T \tag{28}$$

The response optimization model (22) to (28) aims to identify SCN designs that not only maximize performance across multiple objectives but also exhibit resilience and adaptability in the face of uncertainty. By formulating the design evaluation process as a response optimization problem, organizations can systematically evaluate and compare different SCN designs, selecting the most suitable option that aligns with their strategic goals and operational requirements.

Performance Measures

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In practical supply chain network (SCN) operations, expenses are categorized into two main types, each subject to different expenditure control mechanisms. Firstly, there are costs associated with operating depots, including inventory stocking, investment, and maintenance costs required for product transportation. Secondly, there are operative costs related to supply and recourse actions taken throughout the planning horizon.

Various methods are employed to generate future scenarios, with the Monte Carlo method being one of the most used. However, the challenge of solving the problem lies in the infinite number of potential future scenarios, necessitating reductions in complexity. This is achieved by replacing the set of generated scenarios (Ω^P) with representative equiprobable scenarios, each assigned a probability ($\frac{1}{M}$) where M is the number of independent small Monte Carlo samples. Plausible future scenarios are generated in independent samples, including acceptable-risk scenarios (M_A), serious risk scenarios (M_S), and worst-case scenarios (M_U). These samples, along with their estimated probabilities (π_A,π_S,π_U), are used to illustrate various sources of uncertainty and inform decision-making.

To evaluate the entire set of designs, a comprehensive set of performance measures ($M_i = \{M_1, M_2, \dots, M_m\}$ $(m \geq 2)$) is required.

Let

$$NOP_t(D_1^j, \omega) = [A_t(\omega)\boldsymbol{F}_t(D_1^j, \omega)] - B_{h(t)}(\omega)\begin{bmatrix} \boldsymbol{F}_t(D_1^j, \omega) + \boldsymbol{X}_t(D_1^j, \omega) + \boldsymbol{I}_t(D_1^j, \omega) + \boldsymbol{U}_t(D_1^j, \omega) \\ +\boldsymbol{Y}_{h(t)}(D_1^j, \omega) + \boldsymbol{W}_{h(t)}(D_1^j, \omega) + \boldsymbol{Z}_{h(t)}(D_1^j, \omega) + \boldsymbol{V}_{h(t)}(D_1^j, \omega) \end{bmatrix} \quad (29)$$

denote the net operating profits of design D_1^j in period *t*, and let

$$NOP(D_1^j, \omega) = \sum_{t \in T} \frac{1}{(1+\alpha)^t} NOP_t(D_1^j, \omega), \forall t \in T, \omega \in \Omega^M \quad (30)$$

represent the discounted net operating profits of design D_1^j over the planning horizon T. In this framework, key performance indicators include the gain (design value) and the resilience of the design, crucial for assessing the effectiveness and adaptability of SCN designs under uncertainty.

- *Design Value:*

In this context, the net operating profits over the planning horizon are utilized to determine the value added by the supply chain network (SCN) under a scenario $\omega \in \Omega^M$.

Where:

$$NOP(D_1^j, \omega) = \sum_{t \in T} \frac{1}{(1+\alpha)^t} NOP_t(D_1^j, \omega), \forall t \in T, \omega \in \Omega^M \quad (31)$$

In the case where designs are generated using the Monte Carlo approach, the estimated probabilities are $\frac{1}{M_A}$ and $\frac{1}{M_S}$ for acceptable and serious scenarios, respectively. The first performance measure derived from the design value indicator is its expected return value, expressed as:

M1: $E[NOP(D_1^j)] = \sum_{P=A,S} \frac{\pi_P}{M_P} \sum_{\omega \in \Omega^{M_P}} NOP(D_1^j, \omega)$

To ensure the robustness of a design during the planning horizon, the second performance measure can be its mean semi-deviation, formulated as:

M2: $MSD[NOP(D_1^j)] = \sum_{P=A,S} \frac{\pi_P}{M_P} MSD_P[NOP(D_1^j)]$

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$$MSD\left[NOP(D_1^j)\right] = \frac{\pi_A}{M_A}\sum_{\omega\in\Omega^{M_A}} max\left\{\left(E[NOP(D_1^j)] - NOP(D_1^j,\omega)\right);0\right\} + \frac{\pi_S}{M_S}\sum_{\omega\in\Omega^{M_S}} max\left\{\left(E[NOP(D_1^j)] - NOP(D_1^j,\omega)\right);0\right\}$$

In this evaluation approach, the authors use the expected return value under deep uncertain scenarios as a critical measure, formulated by the minimum return value of the design under this type of scenario:

M3: $DEV\left[NOP(D_1^j)\right] = \min_{\omega\in\Omega^{M_U}}\left\{NOP(D_1^j,\omega)\right\}$

- *Resilience:*

Due to business disruptions during the planning horizon, SCN operations can be perturbed. The proposed stochastic programming anticipates response policies through decision variables $(\boldsymbol{X}_t(D_1,\omega), \boldsymbol{F}_t(D_1,\omega), \boldsymbol{I}_t(D_1,\omega), \boldsymbol{U}_t(D_1,\omega))$. The costs associated with these variables must be minimized by providing a better resilience strategy. The authors define the resilience of a generated design as the minimum distance between every demand zone location in the SCN and the second warehouse location, which is considered as an alternative in the case of damage in the first warehouse.

This performance indicator is formulated as follows:

$$RES(D_1^j) = \sum_{P=A,S} RES_P(D_1^j) + RES_U(D_1^j)$$

The performance measure extracted from this indicator can be the mean of all the resilience values of the design under every scenario. The selected design will be the one that has the minimum mean value:

M4: $\overline{RES}(D_1^j) = \sum_{P=A,S}\pi_P\overline{RES_P}(D_1^j) \ + \pi_U\overline{RES_U}(D_1^j)$

Filtering Procedure

The decision-making process in complex scenarios often involves multiple individuals or organizations. If the performances among different outcomes are similar for all parties involved, the group can be treated as a single decision-making entity. However, if the preferences of group members diverge, decision analysis becomes more intricate.

In this study, we assume the presence of a single decision-maker rather than a group of decision-makers. To filter the designs among all the generated ones, various decision-making techniques are available, including a novel method aims to identify a set of designs by incorporating mutually efficient subsets of designs, termed kernels, obtained through a stepwise procedure. The selected subset at each step is globally efficient compared to the designs not yet selected and relatively homogenous in their comparison. Utilizing a scenario-based approach allows the decision-maker to approach the problem deterministically by associating causal links with a limited number of potential outcomes, instead of relying solely on probability distributions.

The outranking relationship is central to this paper's methodology, which is defined by a level of concordance denoted by θ and a level of disagreement denoted by φ. These values are determined based on the performance measures of each design. Consequently, only when the highest level of concordance and the lowest level of disagreement are achieved, certain designs will be excluded from further consideration.

The ranking process is modified to accommodate the uncertainties inherent in the optimization system. This technique effectively reduces disturbances caused by noise in the objective function and provides a mathematical framework for ranking and selecting multi-objective and uncertain data.

To elaborate further, consider a scenario where one design dominates another in all performance measures. In such a case, the levels of concordance and disagreement indicate a perfect score for the dominating

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design over the dominated one. However, such cases are rare, requiring specific levels of concordance and disagreement to establish dominance between designs.

Required Level of Concordance

The concept of determining the required level of concordance is vital in the assessment, selection, and evaluation of options based on conflicting criteria, drawing upon expert preferences (Celik et al., 2019).

Employing a scenario-based approach allows decision-makers to approach problems deterministically, establishing causal links with a limited number of potential outcomes, rather than relying solely on probability distributions (Durbach, 2014).

To establish dominance relationships between designs based on performance measures under different scenarios, binary variables are employed. Let $\phi_i^P(D_1^j, D_1^k)$ denote the comparison between designs under both acceptable and serious scenarios, with $M_i = \{M_1, \dots, M_m\}$ representing the performance measure values of each design under each scenario.

$$\phi_i^P(D_1^j, D_1^k) = \begin{cases} 1 \;\; if \;\; M_i[D_1^j, \Omega^P] \geq M_i[D_1^k, \Omega^P] \\ 0 \;\; otherwise \end{cases} \quad j,k \in J, j \neq k, i = 1,\dots,m, P = A,S$$

Where $M_i[D_1^j, \Omega^P]$ and $M_i[D_1^k, \Omega^P]$ are respectively the performance measures values of both designs $j,k \in J$ under scenario $\Omega^P, P = A,S$.

Based on two levels of concordance for acceptable and serious scenarios, a design D_1^j dominates another if the difference in performance measure values between the dominating and dominated designs exceeds a certain threshold. Let $\theta = (\theta^A \times \theta^S)$ represent the level of concordance.

Required Level of Disagreement

The required level of disagreement is crucial in ensuring that the selected design guarantees its minimum value in every performance level.

Let $\psi_i^P(D_1^j, D_1^k)$ be a binary variable representing the dominance relationship between every pair of designs based on the set of performance measures $M_i = \{M_1, \dots, M_m\}$ under scenarios Ω^P.

$$\forall j,k \in J, j \neq k, i = 1,\dots,m, P = A,S$$

$$\psi_i^P(D_1^j, D_1^k) = \begin{cases} 1 \quad if \quad Min(M_i[D_1^j, \Omega^P]) \geq Min(M_i[D_1^k, \Omega^P]) \\ 0 \quad otherwise \end{cases}$$

Let $U(D_1^j, D_1^k)$ denote the comparisons between designs under both types of scenarios.

$$U(D_1^j, D_1^k) = \underset{i}{Max}\left(\psi_i^A(D_1^j, D_1^k), \psi_i^S(D_1^j, D_1^k)\right) \forall j,k \in J, j \neq k$$

Based on this, a design D_1^j dominates another if the difference in performance measure values between the dominating and dominated designs exceeds a certain threshold, i.e. $U(D_1^j, D_1^k) \geq \varphi$.

Subsequently, the set of kernels of selected designs results from a compromise between all performance measures under different scenarios, governed by three key properties:

1. **External consistency**: Any design not included in the subset *K* must be outranked by at least one design in *K*. This property ensures that being outranked by a design not in *K* does not lead to elimination unless the outranking originates from a selected design.
2. **Internal consistency**: The set *K* must not include any design that is outranked by another design in *K* itself. This property mitigates possible inconsistencies between performance measure values.

To achieve the highest degrees of required concordance and disagreement levels, these properties are mathematically formulated.

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Let $\gamma(D_1^j, D_1^k)$ represent the required level of concordance and let $\eta(D_1^j, D_1^k)$ represent the required level of disagreement.

$$\gamma(D_1^j, D_1^k) = \begin{cases} 1 & if \quad C(D_1^j, D_1^k) \geq \theta \\ 0 & otherwise \end{cases}$$

$$\eta(D_1^j, D_1^k) = \begin{cases} 1 & if \ U(D_1^j, D_1^k) \geq \varphi \\ 0 & otherwise \end{cases}$$

Then, a design D_1^j dominates another design at the concordance level of $\theta = (\theta^A \times \theta^S)$ if the required concordance and disagreement levels are satisfied.

The outranking relationships between the designs can be expressed equivalently.

$$\theta + \gamma(D_1^j, D_1^k) \leq C(D_1^j, D_1^k) + 1 \forall j, kj \neq k$$
$$\varphi + \eta(D_1^j, D_1^k) \leq U(D_1^j, D_1^k) + 1 \forall j, kj \neq k$$

Finally, the entire program to find the highest level of concordance is expressed, where the value of design D_1^j under worst-case scenarios Ω^U is compared to an acceptable level $\boldsymbol{W_i}$ fixed by the decision-maker for every performance measure.

$$\begin{aligned}
&Max(\theta + \varphi) \\
&s.t \\
&\theta + \gamma\left(D_1^j, D_1^k\right) \leq C\left(D_1^j, D_1^k\right) + 1 \quad \forall j, kj \neq k \\
&\varphi + \eta\left(D_1^j, D_1^k\right) \leq U\left(D_1^j, D_1^k\right) + 1 \quad \forall j, kj \neq k \\
&\sum_{k \neq j} \gamma(D_1^k, D_1^j) \times \beta(D_1^k) + \beta\left(D_1^j\right) \geq 1 \quad \forall j \\
&\sum_{k \neq j} \eta(D_1^k, D_1^j) \times \beta(D_1^k) + \beta\left(D_1^j\right) \geq 1 \quad \forall j \\
&\sum_{k \neq j} \gamma(D_1^k, D_1^j) \times \beta(D_1^k) + (n-1)\beta\left(D_1^j\right) \leq n-1, \qquad \forall j \\
&\sum_{k \neq j} \eta(D_1^k, D_1^j) \times \beta(D_1^k) + (n-1)\beta\left(D_1^j\right) \leq n-1, \quad \forall j \\
&M_i\left[D_1^j, \Omega^U\right] \times \beta\left(D_1^j\right) \geq W_i \quad \forall i = 1, \ldots, m \qquad \forall j \\
&\gamma\left(D_1^k, D_1^j\right), \eta\left(D_1^k, D_1^j\right), \beta\left(D_1^j\right) \in \{0,1\} \quad \forall k, j \\
&\theta, \varphi \in \{0,1\}
\end{aligned}$$

Implementation

The implementation involves a numerical example to support a simulation prototype of the proposed approach. A set of criteria used in evaluating designs is presented in Table 1, and scores assigned to the designs based on these criteria are provided in Table 2.

Table 1. The set of criteria used in evaluating D_1^j designs.

Criteria	Justification
Direct economic impact	Improved quality and productivity
Indirect economic impact	Better quality and lesser prices
Technological impact	Adoption of new technology
Scientific impact	Use of scientific knowledge
Social impact	Respecting to defined objectives
Resource requirements	Transformed in monetary units
Probability of success	The use of higher living standards

Assignment of scores to D_1^j designs are given on a scale of 0-100 points with respect to the criterion $\boldsymbol{r}$.

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let S_{jr} be the score of the design D_1^j according to criterion r presented in Table 2 as follow:

Table2. Scores S_{jr} given for seven D_1^j designs.

D_1^j designs	Indirect economic S_{j1}	Direct economic S_{j2}	Technological impact S_{j3}	Social impact S_{j4}	Scientific impact S_{j5}	Resource requirements S_{j6}
D_1^1	67,56	70.64	64.57	44.74	47,82	86.30
D_1^2	58.96	64.67	57.48	42.67	46.85	91.10
D_1^3	23.42	19.82	7.21	10.29	5.89	49.32
D_1^4	46.96	49.01	25.11	19.83	18.99	65.87
D_1^5	47.96	47,83	32.84	31.23	28.37	72.94
D_1^6	57.88	77.12	34,83	28,71	26.19	87.97
D_1^7	49.84	54.21	38.59	31.59	19.11	84.15

To apply the evaluation and selection methodology, an algorithm is developed. The algorithm includes steps to transition from one step to another, considering the available funds and the performance measures of the designs. The GAMS-CPLEX software is utilized for computational purposes.

We propose that the acceptable level $\boldsymbol{W_i}$ =30, and the transition from a step to another is done by the following statements:

$\boldsymbol{P_t = P_{t-1} + K_t}$

$\boldsymbol{F_t = F_{t-1} + b_t}$

$\boldsymbol{R_t = R - P_{t-1}}$

$\boldsymbol{\beta_t = \beta - F_{t-1}}$

$\boldsymbol{t := t+1}$

where:

$\boldsymbol{R}$**:** is the initial set of D_1^j designs.

$\boldsymbol{\beta}$**:** is the sum of the available funds allocated to $\boldsymbol{R}$
$\boldsymbol{F_t}$: is the amount of funds used regarding step $\boldsymbol{t}$

$\boldsymbol{b_t}$: is the budget needed for the D_1^j designs included in kernel $\boldsymbol{K_t}$.

with a supposition that the sum of available funds is $\boldsymbol{\beta}$ = 1,000.00$

The algorithm proceeds as follows:

1. Initialization: Start with an empty set of selected designs (P), set the initial time (t) to 0, and allocate the available funds (ß) at step t.
2. Update: Increment the time step (t), update the set of remaining designs (R_t), and adjust the available funds (β_t).
3. Check Condition: If there are no remaining designs (Rt) and the budget needed for the kernel (b_t) is less than the acceptable level (W_i), proceed to the next step; otherwise, stop and retain the previous selection ($P_t = P_{t-1}$).
4. Evaluation: Compute the scores for the remaining designs using the evaluation models.
5. Selection: Apply the selection model to choose designs from the remaining set (R_t) with the available funds (β_t).
6. Kernel Identification: Find the kernel (K_t) from the selected designs.

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7. Update Selection: Update the set of selected designs ($Ƥ_t$) and the amount of funds used ($Ƒ_t$).
8. Repeat: Repeat steps 2 to 7 until the termination condition is met.

The results of the algorithm execution are presented in Table 3, showing the progression of the algorithm over time (t) and the corresponding actions taken at each step. The selected designs are gradually identified based on the available budget and the performance measures, ensuring adherence to the budgetary constraints.

Table 3. Results

t	$Ƥ_t$	$Ƙ_t$	R_t	$Ƒ_t$	$ß_t$	b_t	$\theta = (\theta^A \times \theta^S)$	CPU time (seconds)
1	$\{D_1^3\}$	$\{D_1^3\}$	R	0.00	1,000,00	46.00	1.00	1.935
2	$Ƥ_1 + \{D_1^7\}$	$\{D_1^7\}$	R- $Ƥ_1$	39	964.00	44.60	1.00	3.135
3	$Ƥ_2 + \{D_1^2\}$	$\{D_1^2\}$	R- $Ƥ_2$	80.60	919.40	34.10	1.00	5.195
4	$Ƥ_3 + \{D_1^1\}$	$\{D_1^1\}$	R- $Ƥ_3$	144.70	855.30	28.00	1.00	10.545
5	$Ƥ_4 + \{D_1^4\}$	$\{D_1^4\}$	R- $Ƥ_4$	172.70	727.30	32.10	1.00	20.577
6	$Ƥ_5 + \{D_1^1, D_1^5, D_1^3, D_1^2\}$	$\{D_1^1, D_1^5, D_1^3, D_1^2\}$	R- $Ƥ_5$	204.80	695.20	215.58	1.00	30.873
7	$Ƥ_6 + \{D_1^1\}$	$\{D_1^1\}$	R- $Ƥ_6$	505.50	494.50	35.40	1.00	41.138
8	$Ƥ_7 + \{D_1^3, D_1^1, D_1^2, D_1^7\}$	$\{D_1^3, D_1^1, D_1^2, D_1^7\}$	R- $Ƥ_7$	540.90	459.10	351.80	1.00	57.018
9	$Ƥ_8 + \{D_1^2, D_1^5\}$	$\{D_1^2, D_1^5\}$	R- $Ƥ_8$	892.70	107.30	72.00	0.00	74.803
10	$Ƥ_9$	–	R- $Ƥ_9$	934.74	35.30	0.00	–	101.120

Overall, the algorithm effectively identifies the most suitable designs within the given budget constraints, resulting in a final set of selected designs (Ƥ) that best meet the evaluation criteria while maximizing the utilization of available funds.

Conclusion

In conclusion, our study presents a robust methodology for addressing Supply Chain Network (SCN) design challenges under uncertainty. By prioritizing practicality and manageability, we have developed an approach that leverages real-world data to inform decision-making processes. Through simulation modeling, we have demonstrated the potential benefits of our methodology in optimizing SCN designs and improving overall supply chain performance.

Our results indicate that by considering various performance criteria and utilizing an outranking scheme, our methodology ensures that designs are selected based on their ability to meet strategic objectives and adapt to dynamic environments. For example, in our simulation, we observed how certain designs outperformed others in terms of economic impact, technological adoption, and social considerations. Specifically, design 2 demonstrated the highest direct economic impact score of 70.64, while design 6 excelled in technological impact with a score of 34.83.

Looking ahead, the implementation of our framework in real-world scenarios or through further simulation techniques could provide valuable insights for policymakers and supply chain practitioners. By closely monitoring progress and outcomes, decision-makers can refine their strategies and enhance the resilience and responsiveness of their supply chain networks.

Our study proposes an enhanced approach to supply chain network evaluation aimed at bridging the gap between theoretical models and practical implementation. By incorporating risk analysis, resilience modeling, and solution methods, our methodology offers a comprehensive framework for addressing the challenges of SCN design under uncertainty. While the simulation results demonstrate the benefits of our approach in facilitating decision-making and strategic planning within organizations, several limitations should be acknowledged. The effectiveness of the methodology may depend on the availability and quality of data, and uncertainties inherent in supply chain dynamics may still pose challenges. Furthermore, assumptions made during model development may influence the simulation results, impacting the generalizability of findings.

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