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A Scenario-Based Stochastic MILP Model for Sustainable Reconfiguration of Smart Grids in the Electricity Supply Chain under Uncertainty

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ABSTRACT

Objective: This study develops a sustainable reconfiguration framework for smart grids in electricity supply chain networks under uncertainty. The research aims to integrate strategic redesign and operational decisions while simultaneously addressing economic and environmental objectives.

Methods: A two-stage scenario-based stochastic mixed-integer linear programming (MILP) model is developed to minimize total network cost and greenhouse gas emissions under uncertain electricity demand and selling prices. The bi-objective model is solved using the augmented epsilon-constraint (AUGMECON) method to generate Pareto-efficient solutions. Stochastic performance measures, including the Value of the Stochastic Solution (VSS) and Expected Value of Perfect Information (EVPI), are also employed to evaluate the value of considering uncertainty.

Results: The results show that explicitly incorporating uncertainty changes the trade-off between economic and environmental objectives and leads to redesign strategies that outperform deterministic solutions under different operating conditions. Electricity demand has a greater influence on network cost than electricity selling price, while the transmission and distribution loss coefficient is identified as the most influential parameter affecting economic performance. The VSS confirms the economic benefit of explicitly considering uncertainty, while the EVPI demonstrates the value of improved information for redesign decisions.

Conclusion: The study integrates strategic reconfiguration decisions, including the installation and closure of generation and distributed generation facilities, with operational decisions on electricity generation, pricing, load allocation, and capacity planning within a unified stochastic framework. The proposed approach provides decision support for coordinated and sustainable smart grid reconfiguration under uncertain operating conditions.

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1. Introduction

The increasing electrification of modern societies, together with population growth, economic development, and rising living standards, continues to drive global electricity demand. At the same time, a substantial share of electricity generation remains dependent on fossil-fuel-based resources, making the electricity sector one of the major contributors to greenhouse gas (GHG) emissions worldwide (Jabbarzadeh et al., 2019). These challenges have intensified the need for electricity systems that can simultaneously improve operational efficiency, ensure reliable energy supply, and reduce environmental impacts.

Smart grids have emerged as a promising solution to address these challenges. Unlike traditional electricity networks, which rely on a unidirectional flow of electricity from centralized generators to end users, smart grids support bidirectional power flows, distributed energy resources, demand-side management programs, and active consumer participation through prosumers (Momoh, 2012; Alvarez et al., 2024). The integration of these capabilities can improve network flexibility, reduce transmission losses, enhance system resilience, and facilitate the transition toward more sustainable electricity systems.

As electricity networks evolve, utilities and policymakers increasingly face the challenge of adapting existing infrastructures to changing market conditions, technological developments, and environmental requirements. In many situations, constructing an entirely new network is neither economically feasible nor operationally desirable. Consequently, network reconfiguration or redesign has become an important strategic decision. In redesign problems, an existing network is modified through decisions such as facility installation, facility closure, capacity adjustment, and resource reallocation in order to improve overall performance (Hammami & Frein, 2014). Previous studies have shown that redesign decisions can substantially reduce operating costs while improving network efficiency and environmental performance.

The need for research in this area extends beyond addressing an academic gap. Electricity infrastructure is highly capital-intensive and is expected to operate for several decades, making the replacement of existing networks economically impractical in most cases. Consequently, utilities are increasingly required to reconfigure existing networks rather than construct new ones. This challenge has become more pronounced with the growing penetration of distributed energy resources and microgrids, which fundamentally change traditional power flow patterns and require existing infrastructures to be adapted accordingly. At the same time, strategic redesign decisions, such as installing or retiring generation assets, are costly and difficult to reverse once implemented. Making these decisions without explicitly accounting for future uncertainty in electricity demand and market conditions may result in inefficient investments, higher operating costs, and reduced environmental performance. These practical challenges highlight the need for integrated optimization models capable of supporting long-term redesign decisions under uncertainty.

Despite significant progress in smart grid planning and electricity supply chain optimization, several research gaps remain. First, most studies focus on the design of new electricity networks rather than the reconfiguration of existing smart grids. Second, redesign decisions are rarely integrated with operational decisions such as electricity generation, load allocation, pricing policies, and generation capacity planning within a unified optimization framework. Third, although uncertainty is an inherent characteristic of electricity systems due to fluctuations in demand, market conditions, and energy prices, the combined effects of uncertainty and network redesign have received limited attention in the context of sustainable smart grids. Finally, the simultaneous consideration of economic and environmental sustainability objectives within a stochastic smart grid reconfiguration framework remains underexplored.

Addressing these challenges is closely aligned with several United Nations Sustainable Development Goals (SDGs). The proposed framework primarily contributes to SDG 7 (Affordable and Clean Energy) by improving the efficiency and flexibility of electricity systems and facilitating the integration of distributed energy resources. It also supports SDG 9 (Industry, Innovation and Infrastructure) through infrastructure reconfiguration and resilient network planning, SDG 11 (Sustainable Cities and Communities) by promoting more reliable and sustainable urban electricity systems, and SDG 13 (Climate Action) by explicitly incorporating greenhouse gas emission reduction into the optimization model. These SDGs provide an appropriate sustainability context for the proposed electricity supply chain redesign framework.

To address the identified research gaps, this study develops a scenario-based stochastic mixed-integer linear programming (MILP) model for the sustainable reconfiguration of smart grids in electricity supply chain networks. The proposed model simultaneously minimizes total network costs and greenhouse gas emissions while considering uncertainty in electricity demand and selling prices. Reconfiguration decisions include the installation and closure of generators and distributed generation units, while operational decisions encompass electricity generation, load allocation, electricity pricing, and capacity planning. The resulting bi-objective stochastic model is solved using the Augmented ε-Constraint (AUGMECON) method to generate efficient Pareto-optimal solutions. The main contributions of this study are summarized as follows:

- A scenario-based stochastic MILP model is developed for the sustainable reconfiguration of smart grids in electricity supply chain networks under uncertainty;
- Strategic reconfiguration decisions, including the installation and closure of generators and distributed generation units, are integrated with operational decisions related to electricity generation, pricing, load allocation, and capacity planning within a unified framework;
- Economic and environmental sustainability objectives are simultaneously considered through a bi-objective optimization model that minimizes total costs and greenhouse gas emissions;
- Demand uncertainty and electricity price uncertainty are explicitly incorporated using a scenario-based stochastic programming approach;
- The effectiveness of the proposed framework is evaluated using the AUGMECON method and stochastic performance measures, providing insights into the value of accounting for uncertainty in smart grid reconfiguration decisions.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature and identifies the research gap. Section 3 presents the problem description and mathematical formulation. Section 4 describes the solution strategy. Section 5 reports the computational results and analyses. Finally, Section 6 concludes the study and outlines future research directions.

2. Literature Review

Research on electricity supply chain networks has expanded considerably over the past two decades, driven by the increasing penetration of renewable energy resources, smart grid technologies, and sustainability concerns. Existing studies can generally be classified into three closely related streams: sustainable supply chain network design, electricity supply chain planning and smart grids, and supply chain network reconfiguration. Although these streams have evolved independently, they collectively provide the theoretical foundation for developing integrated optimization models for sustainable electricity supply chains. Table 1 summarizes representative studies and highlights the main characteristics of the proposed model.

2.1 Sustainable Supply Chains and Electricity Networks

Studies on sustainable supply chain network design primarily focus on incorporating environmental objectives, renewable energy resources, and uncertainty into strategic planning. Lotfi et al. (2021) demonstrated that integrating renewable energy into supply chain networks improves resilience against demand fluctuations while supporting sustainability objectives. Similarly, Liu et al. (2021) investigated sustainable supply chain management in emerging markets and highlighted the importance of considering sustainability under different operating conditions. Belhadi et al. (2022) emphasized the role of big data analytics in improving sustainability performance and operational efficiency through data-driven decision-making. From an optimization perspective, Ahn et al. (2015) developed a deterministic model for designing a biomass-to-biodiesel supply chain, whereas Bairamzadeh et al. (2018), Khishtandar (2019), and

Shahbazbegian et al. (2020) incorporated different uncertainty handling approaches, including robust and fuzzy programming, into renewable energy supply chain design.

Another stream of research investigates electricity supply chains and smart grid planning. Nagurney and Matsypura (2011) introduced the supply chain perspective into electricity networks and established the theoretical basis for modeling interactions among electricity market participants. Subsequent studies incorporated market structures, emission regulations, and operational constraints into electricity supply chain models (Lai et al., 2009a; Lai et al., 2009b; Oliveira et al., 2013; Chen et al., 2014). More recent studies have shifted toward sustainable smart grids under uncertainty. Osmani and Zhang (2014) considered renewable energy resources together with uncertain wind speed and electricity prices. Khosrojerdi et al. (2016) proposed a robust optimization model for generation and transmission planning under electricity price uncertainty. Jabbarzadeh et al. (2019) incorporated resilience, demand-side management, and microgrid structures into a stochastic smart grid design model. Bayatloo and Bozorgi-Amiri (2019) developed a two-stage stochastic model for dynamic electricity network planning, while Hosseini-Motlagh et al. (2020) integrated sustainability objectives, distributed generation, and uncertainty into multi-objective optimization models. Recent review and methodological studies have further emphasized resilience, digitalization, and advanced analytical techniques for electricity supply chains (Hinton et al., 2022; Hosseini & Ivanov, 2020; Kosasih & Brintrup, 2021).

A third research stream addresses supply chain network reconfiguration, where the objective is to redesign existing networks rather than establish new ones. Hammami and Frein (2014) proposed a comprehensive optimization framework for global supply chain redesign, while Paz et al. (2015) considered demand variability in strategic redesign decisions. Khosravi et al. (2017), Fattahi et al. (2018), and Jahani et al. (2018, 2019) investigated redesign decisions under uncertain demand and price conditions by integrating strategic and tactical decisions such as pricing and capacity planning. More recently, Ivanov and Dolgui (2020) incorporated sustainability, resilience, robustness, and risk aversion into supply chain redesign using a two-stage mixed-integer programming model. Van Engeland et al. (2020), Lotfi et al. (2021), Abbasi and Ahmadi Choukolaei (2023), and Abbasi and Erdebilli (2023) further demonstrated the growing importance of environmental regulations, renewable energy integration, and digital technologies in redesigning sustainable supply chain networks.

2.2 Research Gap

As summarized in Table 1, previous studies have made important contributions to sustainable electricity supply chains, smart grid planning, and supply chain network reconfiguration. However, these research streams have largely evolved independently, and no existing study simultaneously integrates smart grid reconfiguration, strategic redesign decisions, operational planning, sustainability objectives, and uncertainty within a unified optimization framework. Consequently, several important research gaps remain.

First, most studies on electricity supply chains focus on designing or expanding new networks, whereas the reconfiguration of existing smart grids has received considerably less attention. Strategic decisions such as simultaneously installing and closing conventional generators and distributed generation units have rarely been incorporated into electricity supply chain optimization models.

Second, although sustainability and uncertainty have frequently been considered, they are usually investigated separately from network reconfiguration decisions. Few studies simultaneously optimize economic and environmental objectives while redesigning existing smart grids under uncertain operating conditions.

Third, previous research generally concentrates on a limited subset of operational decisions, such as electricity generation, pricing, capacity expansion, or facility location. An integrated framework that simultaneously determines network reconfiguration, electricity generation, load allocation, electricity pricing, and generation capacity under uncertainty is still lacking.

To address these gaps, this study proposes a scenario-based stochastic mixed-integer linear programming model for sustainable smart grid reconfiguration. Therefore, unlike previous studies summarized in Table 1, the proposed framework integrates strategic network reconfiguration decisions (generator installation and closure), distributed generation deployment, electricity generation, load allocation, electricity pricing, and capacity planning within a scenario-based stochastic bi-objective MILP model that simultaneously minimizes total cost and greenhouse gas emissions. AUGMECON method is then employed to generate Pareto-efficient solutions for sustainable electricity supply chain reconfiguration under uncertainty.

Table 1. Comparison of representative studies with the proposed research

Study	Sustainable electricity supply	Smart grid / microgrid	Network reconfiguration	Sustainability objectives	Uncertainty	Pricing decision	Capacity planning	Solution approach	Main limitation
Nagurney & Matsypura (2007)	✓	–	–	–	–	–	–	Supply chain equilibrium	Strategic redesign not considered
Osmani & Zhang (2014)	✓	✓	–	–	✓	✓	✓	Stochastic programming	No network reconfiguration
Khosrojerdi et al. (2016)	✓	✓	–	✓	✓	–	✓	Robust optimization	Operational decisions limited
Jabbarzadeh et al. (2019)	✓	✓	–	✓	✓	–	✓	Stochastic programming	Existing network redesign ignored
Bayatloo & Bozorgi-Amiri (2019)	✓	✓	–	–	✓	–	✓	Two-stage stochastic programming	Sustainability not explicitly addressed
Hosseini-Motlagh et al. (2020)	✓	✓	–	✓	✓	–	✓	Fuzzy-robust optimization	Existing network reconfiguration not considered
Hammami & Frein (2014)	–	–	✓	–	–	–	✓	MILP	Not developed for electricity networks
Khosravi et al. (2017)	–	–	✓	–	✓	✓	✓	MILP	Sustainability not considered
Fattahi et al. (2018)	–	–	✓	–	✓	✓	✓	Multi-period optimization	Electricity systems not considered
Jahani et al. (2018, 2019)	–	–	✓	Partial	✓	✓	✓	Stochastic optimization	Not applicable to smart grids
Ivanov & Dolgui (2020)	–	–	✓	✓	✓	–	✓	Two-stage MILP	Electricity-specific decisions omitted
This study	✓	✓	✓	✓	✓	✓	✓	Scenario-based stochastic MILP solved by the AUGMECON	Addresses the identified research gaps

3. Model Formulation

Electricity supply chain networks comprise three interrelated subsystems: generation, transmission, and distribution. The generation subsystem includes conventional and renewable power plants that produce electricity to satisfy consumer demand. Electricity is transferred through the transmission subsystem via high-voltage transmission lines and is subsequently delivered to end users through the distribution subsystem. High-voltage transmission lines are assumed to experience distance-dependent power losses, whereas local distribution lines are considered lossless because of their relatively short transmission distances (Jabbarzadeh et al., 2019).

The proposed network incorporates smart grid capabilities that enable bidirectional electricity flows between consumers and the network. As illustrated in Fig. 1, consumers equipped with distributed energy resources can both purchase electricity from the grid and sell surplus electricity back to the network. Such interactions are facilitated through microgrids, which are defined as localized groups of interconnected loads and distributed energy resources capable of operating either in grid-connected or islanded mode (Pullins, 2019). Distributed generation technologies, including photovoltaic systems, allow electricity to be generated close to consumption points, thereby improving service reliability, reducing transmission losses, and enhancing network resilience, particularly during disruptive events (Jabbarzadeh et al., 2019; Konidena et al., 2020). In the proposed network, fossil-fuel and renewable power plants located at supply nodes are referred to as generators, whereas distributed energy resources installed at demand nodes are referred to as distributed generators.

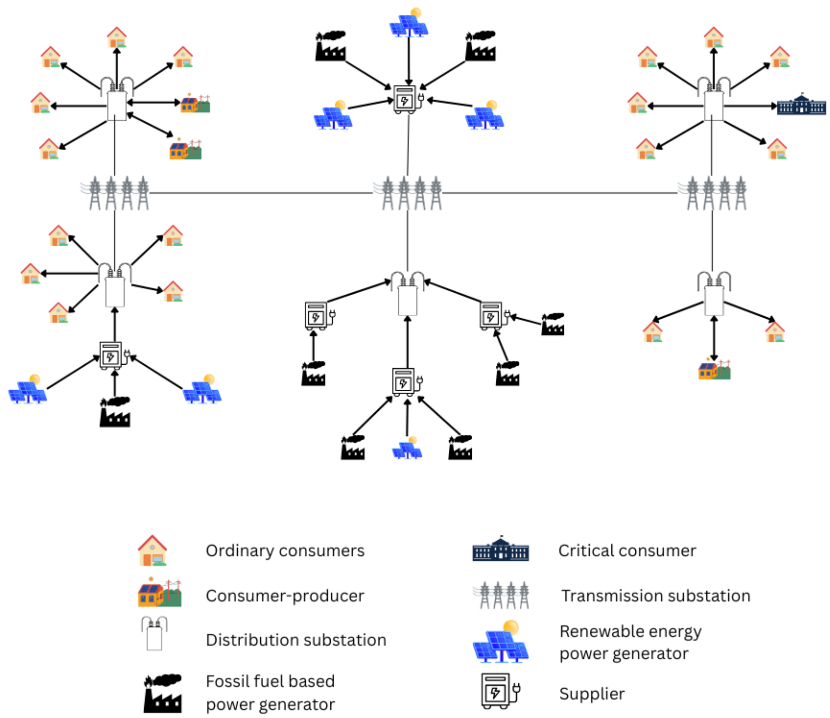

Figure 1. Overview of the proposed smart grid network

The reconfiguration of an existing smart grid is formulated as a multi-period, bi-objective optimization problem that simultaneously considers strategic redesign and operational planning decisions. The strategic level determines long-term network reconfiguration decisions, including the installation or closure of generators and distributed generators, as well as the installation of microgrid equipment and transmission substations. Once these strategic decisions are implemented, operational decisions are optimized for each planning period and uncertainty scenario. These decisions include electricity generation, load allocation, electricity pricing, and generation capacity. The two objective functions minimize the total economic cost and greenhouse gas emissions, respectively.

To represent uncertainty, a scenario-based two-stage stochastic programming framework is adopted. In this framework, strategic redesign decisions constitute the first-stage variables and are determined before the realization of uncertain parameters. After the uncertainty is revealed, second-stage operational decisions are optimized independently for each scenario while satisfying the same strategic configuration determined in the first stage. Uncertainty is represented through a finite set of scenarios associated with electricity demand and selling price, each characterized by a known occurrence probability. Consequently, the objective function minimizes the expected total system cost over all scenarios while simultaneously minimizing total greenhouse gas emissions. This modeling framework enables the proposed network to explicitly account for uncertainty without imposing the conservatism associated with robust optimization approaches.

The proposed formulation is developed based on the following assumptions.

- Redesign decisions are limited to the installation and closure of generators at supply nodes and distributed generators at demand nodes;
- Due to the substantial investment required, installed generators and distributed generators cannot be temporarily closed and subsequently reopened during the planning horizon.;
- The number of facilities that may be installed or closed in each planning period is limited.;
- All strategic decisions are implemented at the beginning of each planning period;
- Once a generator or distributed generator is installed (or closed), its operational status remains unchanged throughout the remaining planning horizon;
- The total number of status changes for generators and distributed generators is limited over the planning horizon;
- All customer demand must be satisfied; therefore, shortages are not permitted.

The notation used in the mathematical formulation is summarized in the following. For clarity, the notation is grouped into sets, parameters, and decision variables.

Sets	
EI	Set of generators available at the beginning of the planning horizon
PI	Set of potential locations for installing generators at node i
$\mathrm{I} = \mathrm{EI} \cup \mathrm{PI}$	Set of suppliers (i= 1, ..., I)
EG	Distributed generation available at the beginning of the planning horizon
PG	Set of potential locations for installing new distributed generation at node j
$G = EG \cup PG$	Set of customers (j = 1, ..., J)
$N = I \cup G$	Set of all points (including suppliers and customers)
T	Set of time periods for strategic decisions (t = 1, ..., T)
T'	Set of time intervals for operational decisions (t'= 1, . . ., T')
K	Set of generator types (k = 1, ..., K)
S	Set of scenarios ($s = 1, \dots, S$)

Parameters	
$\mathrm{d_{ij}}$	Distance between nodes i and j
$\mathrm{E_k}$	GHG emissions per unit of power generation at generator type k
$\mathrm{vc_{ktt'}}$	Unit variable cost of production by generator k of node i in time interval $\mathrm{t}' \in \mathrm{T}'$ and period $\mathrm{t} \in \mathrm{T}$
$\mathrm{sfc_i}$	Fixed cost of installing generator k at node i
$\mathrm{gfc_j}$	Fixed cost of installing distributed generators at node j
$\mathrm{dfc_i}$	Fixed cost of closing generator k at node i
$\mathrm{pfc_j}$	Fixed cost of closing distributed generator k at node j
$\mathrm{mfc_j}$	Fixed cost of installing transmission substation and other microgrid equipment at node j
u	Number of times allowed to install or close generators over the planning horizon
F	Number of times allowed to install or close distributed generators over the planning horizon
γ	Penalty cost for unmet demand
Lc	Coefficient of loss in transmission/distribution networks
β	Maximum allowable price discrimination
$\mathrm{pri_t}$	Base unit-selling price for time interval $\mathrm{t}' \in \mathrm{T}'$ and period $\mathrm{t} \in \mathrm{T}$
τ_i	User-defined constants, $\tau_\mathrm{i} \in (0,1], \mathrm{i} = 1,2,3$
$\mathrm{O_t}$	Total budget available in period $\mathrm{t} \in \mathrm{T}$ for expenditures on facility location
$\mathrm{ECap_{ik}}$	Maximum nominal expansion capacity of generator type k at node i
$\mathrm{GCap_{jk}}$	Maximum nominal distributed generation capacity of type k at node j
$\mathrm{TCap_i}$	Maximum capacity at transmission substation i

Scenario- based parameters

$pr_{tt's}$	Unit selling price in time interval $t' \in T'$ and period $t \in T$ under scenario s
$D_{jtt's}$	Demand of node j in time interval $t' \in T'$ and period $t \in T$ under scenario s
ρ_s	Probability of each scenario s

Decision variables

$x_{ijk}^{tt's}$	Amount of power generated by the kth generator of supplier i to be consumed by node j in time interval $t' \in T'$ and period $t \in T$ (delivered using high-voltage transmission lines) under scenario $s \in S$
$y_{ijk}^{tt's}$	Amount of power generated by the kth generator of supplier i to be consumed by node j in time interval $t' \in T'$ and period $t \in T$ (delivered using low-voltage local distribution lines) under scenario $s \in S$
$g_{jktt's}$	Amount of power generated by distributed generator type k at node j in time interval $t' \in T'$ and period $t \in T$ under scenario $s \in S$
e_{ikts}	Generation capacity of generator k at node i in period $t \in T$ under scenario $s \in S$
q_{jkts}	Generation capacity of distributed generator k at node j in period $t \in T$ under scenario $s \in S$
z_{jt}	$\begin{cases} 1 & \text{if transmission substation and and other microgrid equipment are installed in node j in period } t \in T \\ 0 & \text{Otherwise} \end{cases}$
n_{kit}	$\begin{cases} 1 & \text{if the status of generators at node i changes in period } t \in T \\ 0 & \text{Otherwise} \end{cases}$ n_{kit}= 1 means that a new generator k is installed in site i in period $t \in T$; for $i \in PI$ n_{kit} = 1 means that the initially existing generators k in site i is closed in period $t \in T$; for $i \in EI$
m_{kjt}	$\begin{cases} 1 & \text{if the status of distributed generators at node j changes in period } t \in T \\ 0 & \text{Otherwise} \end{cases}$ m_{kjt}= 1 means that a new distributed generators is installed in site j in period $t \in T$; for $j \in PG$ m_{kjt} = 1 means that the initially existing distributed generators j is closed in period $t \in T$; for $j \in EG$
δ_t	Deviation from the reference budget o_t in period $t \in T$
$\theta_{tt's}$	Linearization variable under scenario $s \in S$

Based on the above assumptions and notation, the proposed scenario-based stochastic mixed-integer linear programming (MILP) formulation is presented as follows.

$$Min\ f_1 = \sum_{k\in K}\sum_t\left(\sum_{i\in PI} sfc_{ik}n_{kit} + \sum_{i\in EI} dfc_{ik}n_{kit} + \sum_{j\in PG} gfc_{jk}\, m_{kjt} + \sum_{j\in EG} pfc_{jk}m_{kjt}\right) + \sum_{j\in G}\sum_{t\in T} mfc_j z_{jt} - \sum_{s\in S}\rho_s\Big[\sum_{i\in I}\sum_{j\in G}\sum_{k\in K}\sum_{t\in T}\sum_{t'\in T} pr_{tt's}\left(x_{ijk}^{tt's}\left(1-\left(lc\times d_{ij}\right)\right) + y_{ijk}^{tt's}\right) - \left(\sum_{j\in G}\sum_{k\in K}\sum_{t\in T}\sum_{t'\in T} g_{jktt's}pri_t\right) + \gamma\sum_{j\in G}\sum_{t\in T}\sum_{t'\in T}[D_{jtt's} - (\sum_{i\in I}\sum_{k\in K}\sum_{t\in T}\sum_{t'\in T} x_{ijk}^{tt's}(1-(lc\times d_{ij})) + y_{ijk}^{tt's}) + 2\theta_{tt's}) + \sum_{i\in I}\sum_{j\in G}\sum_{k\in K}\sum_{t\in T}\sum_{t'\in T} vc_{ktt'}\left(x_{ijk}^{tt's} + y_{ijk}^{tt's}\right) + \sum_{j\in G}\sum_{k\in K}\sum_{t\in T}\sum_{t'\in T} vc_{ktt'}g_{jktt's}\Big] \tag{1}$$

$$Min\ f_2 = \sum_{s\in S}\rho_s\left(\sum_{i\in I}\sum_{j\in G}\sum_{k\in K}\sum_{t\in T}\sum_{t'\in T} E_k\left(x_{ijk}^{tt's} + y_{ijk}^{tt's}\right)\right) \tag{2}$$

S.t.

$$\sum_{j\in G}\left[D_{jtt's} - \sum_{i\in I}\sum_{k\in K}\left(x_{ijk}^{tt's}\left(1-lc\times d_{ij}\right) + y_{ijk}^{tt's}\right)\right] - \theta_{tt's} \geq 0 \qquad \forall t\in T, t'\in T', s\in S \tag{3}$$

$$\sum_{j\in G}\sum_{t'\in T}\left(x_{ijk}^{tt's} + y_{ijk}^{tt's}\right) \leq e_{ikts} \qquad \forall\, i\in I, k\in K, t\in T, s\in S \tag{4}$$

$$g_{jktt's} \leq q_{jkts} \qquad \forall\, t\in T, t'\in T', j\in G, s\in S, k\in K \tag{5}$$

$$\sum_{t\in T} n_{kit} \leq u \qquad \forall i\in I, k\in K \tag{6}$$

$$\sum_{t\in T} m_{kjt} \leq f \qquad \forall j\in G, k\in K \tag{7}$$

$$\sum_{i\in I}\sum_k n_{kit} \leq \tau_1|I| \qquad \forall t\in T \tag{8}$$

$$\sum_{j\in G}\sum_{k\in K} m_{kjt} \leq \tau_1|G| \qquad \forall t\in T \tag{9}$$

$$m_{kjt} \leq z_{jt} \qquad \forall j \in PG, k \in K, t \in T \qquad (10)$$

$$q_{jkts} \leq GCap_{jk} m_{kjt} \qquad \forall j \in PG, k \in K, t \in T, s \in S \qquad (11)$$

$$q_{jkts} \leq GCap_{jk} - GCap_{jk} m_{kjt} \qquad \forall j \in EG, k \in K, t \in T, s \in S \qquad (12)$$

$$e_{ikts} \leq ECap_{ik} n_{kit} \qquad \forall i \in PI, k \in K, t \in T, s \in S \qquad (13)$$

$$e_{ikts} \leq ECap_{ik} - ECap_{ik} n_{kit} \qquad \forall i \in EI, k \in K, t \in T, s \in S \qquad (14)$$

$$\sum_{i \in PI} \sum_{k \in K} sfc_{ik}\, n_{kit} + \sum_{i \in EI} \sum_{k \in K} dfc_{ik} n_{kit} + \sum_{j \in PG} \sum_{k \in K} gfc_{jk}\, m_{kjt} + \sum_{j \in EG} \sum_{k \in K} pfc_{jk} m_{kjt} + \delta_{t-1} + \delta_t = O_t \qquad \forall t \in T \qquad (15)$$

$$\sum_{j \in G} \sum_{k \in K} x_{ijk}^{tt's} \leq TCap_i \qquad \forall\, i \in I, t \in T, t' \in T', s \in S \qquad (16)$$

$$\sum_{j \in G} \sum_{i \in I} \sum_{k \in K} \left[x_{ijk}^{tt's} \left(1 - \left(lc \times d_{ij} \right) \right) + y_{ijk}^{tt's} \right] + \sum_{k \in K} g_{jktt's} \geq D_{jtt's} \qquad \forall\, t \in T, t' \in T', s \in S \qquad (17)$$

$$(1-\beta) pri_t \leq \frac{\sum_{i \in I} \sum_{k \in K} pr_{tt's} \times \left(x_{ijk}^{tt's} + y_{ijk}^{tt's} \right)}{D_{jtt's}} \leq (1+\beta) pri_t \qquad \forall\, j \in G, t \in T, t' \in T', s \in S \qquad (18)$$

$$x_{ijk}^{tt's}, y_{ijk}^{tt's}, g_{jktt's}, e_{ikts}, q_{jkts} \geq 0 \qquad \forall i \in I, j \in G, k \in K, t \in T, t' \in T', s \in S \qquad (19)$$

$$z_{jt}, n_{kit}, m_{kjt} \in 0,1 \qquad \forall i \in I, j \in G, k \in K, t \in T \qquad (20)$$

$$\delta_t\!: free \qquad \forall t \in T \qquad (21)$$

The first objective function (1) minimizes the expected total cost of the electricity supply chain network over all scenarios. It includes five major cost components: (I) fixed costs associated with installing and closing generators and distributed generators, (II) investment costs for transmission substations and microgrid infrastructure, (III) revenues obtained from electricity sales, represented as negative costs, (IV) penalty costs associated with demand-supply imbalance, and (V) variable electricity generation costs. The demand-supply imbalance (DSI) term is incorporated to support demand-side management by penalizing deviations between electricity supply and demand. This mechanism discourages both unmet demand and excessive generation, thereby improving the operational efficiency of the network (Jabbarzadeh et al., 2019). Furthermore, transmission losses are explicitly incorporated into the revenue calculation through the distance dependent loss coefficient.

The second objective function (2) minimizes the expected greenhouse gas (GHG) emissions generated by conventional power plants over the planning horizon. Since distributed generators are assumed to be renewable technologies, their emissions are neglected in the environmental objective.

The constraints define the feasible operating region of the proposed two-stage stochastic optimization model. Constraint (3) controls the demand–supply imbalance in each scenario. Constraints (4) and (5) ensure that electricity generation by conventional and distributed generators does not exceed the available generation capacities. Constraints (6) and (7) limit the status of each generator and distributed generator to change at most once during the planning horizon, thereby preventing reopening after closure or reclosing after installation.

Constraints (8) and (9) restrict the maximum number of network reconfiguration actions that can be implemented during each planning period. Constraint (10) guarantees that distributed generators can only be installed if the corresponding microgrid infrastructure is available. Constraints (11)-(14) impose upper bounds on the installed capacities of distributed generators and conventional generators according to their nominal capacity limits.

Constraint (15) enforces the available investment budget in each planning period. Constraint (16) limits the electricity transmitted from each supplier according to the capacity of its transmission substation. Constraint (17) guarantees that the total electricity supplied to each demand node, after accounting for transmission losses and local distributed generation, satisfies the corresponding electricity demand under every scenario.

Constraint (18) limits electricity price discrimination by ensuring that the selling price at each demand node remains within the allowable deviation from the base electricity price. Finally, Constraints (19)-(21) define the domains of the decision variables by enforcing non-negativity for continuous variables, binary requirements for strategic decisions, and unrestricted values for the budget deviation variable.

4. Solution Strategy

The proposed model is formulated as a bi-objective mixed-integer stochastic programming problem with two conflicting objectives: minimizing the total network cost and minimizing greenhouse gas emissions. Because improvements in one objective generally lead to deterioration in the other, a single optimal solution does not exist. Instead, the solution consists of a set of Pareto-efficient solutions that represent different trade-offs between economic and environmental performance. Therefore, an appropriate multi-objective optimization technique is required to generate the Pareto frontier.

Among the available exact multi-objective optimization approaches, the AUGMECON method proposed by Mavrotas (2009) has been widely adopted because of its ability to generate efficient Pareto solutions while avoiding weakly efficient points that frequently appear in the conventional ε-constraint method. In addition, the method requires only minor modifications to the original mathematical formulation, making it particularly suitable for mixed-integer programming models such as the one proposed in this study (Gazijahani et al., 2020; Moslehi et al., 2021; Heydari et al., 2025).

In the proposed solution procedure, the first objective function (total network cost) is selected as the primary optimization objective, whereas the second objective (greenhouse gas emissions) is converted into an ε-constraint. By systematically varying the ε value within its feasible range, a complete set of Pareto-efficient solutions can be generated. Each solution represents a different compromise between cost and environmental performance, allowing decision-makers to select the redesign strategy that best satisfies their planning objectives.

The implementation of the AUGMECON method consists of three main steps:

1. Construct the payoff table by optimizing each objective individually,
2. Determine the feasible range of the ε parameter using the payoff table,
3. Solve the augmented AUGMECON model repeatedly for different ε values to generate the Pareto frontier.

The first step is to determine the individual optimum of each objective function by solving the following optimization problem.

$$\begin{aligned} &\mathrm{Payoff}\ \mathrm{f_{jj}} = \mathrm{Min}\ \mathrm{f_j(x)} \\ &x \in X \end{aligned} \tag{27}$$

The optimal value obtained for objective (j) is stored in the payoff table as ($Payoff_{jj}$). Subsequently, the remaining objective values are calculated while fixing objective (j) at its optimal value, resulting in

$$\begin{aligned} &Payofff_{ij} = Minf_i(x) \\ &f_j(x) = Payofff_{jj} \\ &x \in X \\ &j \neq i \end{aligned} \tag{28}$$

Repeating this process for all objectives produces the payoff matrix

$$Payofff = \left[PayOff\ f_{ij}\right] \tag{29}$$

From the payoff matrix, the minimum value, maximum value, and range of each objective are obtained as

$$\text{Min}\ (f_i) = Min_j\ \{\ PayOff\ f_{ij}\} =\ PayOff\ f_{ii} \tag{30}$$

$$\text{Max}\ (f_i)= Max_j\ \{PayOff\ f_{ij}\} \tag{31}$$

$$\text{R}\ (\ f_i\ ) = \text{Max}\ (\ f_i\ ) - \text{Min}\ (f_i\ ) \tag{32}$$

The obtained ranges define the admissible interval of the ε parameter and are also used to normalize the objectives during optimization. This normalization improves numerical stability and prevents scaling differences between the objective functions from influencing the search process.

Finally, the AUGMECON model is formulated as follows.

$$\begin{aligned} &\mathrm{Min} \mathrm{f_1(x)} - \textstyle\sum_{\mathrm{i=2}}^{\mathrm{m}} \varphi_{\mathrm{i}} \mathrm{s_i} \\ &\mathrm{(x)} - \mathrm{s_i} = \varepsilon_2 \\ &\mathrm{x} \in \mathrm{X} \\ &\mathrm{s_i} \geq 0 \end{aligned} \tag{33}$$

where s_i denotes the non-negative slack variable introduced to eliminate weak Pareto-optimal solutions, while $\varphi_i = R(f_1)/R(f_i)$ is the normalization coefficient calculated from the payoff ranges. For each ε value within its admissible interval, the optimization model is solved once, producing one Pareto-efficient solution. Repeating this procedure over the entire ε range generates the complete Pareto frontier used in the numerical analysis presented in the next section.

5. Application and Results

A numerical example was developed to demonstrate the applicability of the proposed model for redesigning sustainable electricity supply chain networks under uncertainty. The obtained results are first presented and discussed, followed by a sensitivity analysis to evaluate the effect of key model parameters on the model performance.

5.1 Computational Results

A numerical example was developed to demonstrate the applicability of the proposed model for redesigning sustainable electricity supply chain networks under uncertainty. The obtained results are first presented and discussed, followed by a sensitivity analysis to evaluate the effect of key model parameters on model performance.

The test network consists of six supply nodes, six demand nodes, three generation technologies, two strategic planning periods, and two operational time intervals. Existing generation facilities and candidate locations for new generators were simultaneously considered to capture redesign decisions involving facility installation, retirement, distributed generation deployment, and microgrid development. To represent uncertainty, nine scenarios were defined based on different combinations of electricity demand and electricity selling price levels (low, medium, and high). The base scenario corresponds to the medium level of both uncertain parameters, while the remaining scenarios represent ±10% variations around the base values. Each scenario was assigned a predefined probability, and the corresponding probabilities were incorporated into the stochastic objective function. The numerical values of the model parameters are summarized in Table 2. The scenario probabilities are reported in Table 5.

Table 2. Parameter values for the numerical example

Parameters	values	Parameters	Values
dis(i, j)	Uniform(20,99)	$Ecap(i,k)$	Uniform(1020000,1050000)
Vc(k, t, t′)	Uniform(10000,40000)	Gcap(j, k)	Uniform(50,800)
sfc(i)	Uniform(1000,2000)	γ	Uniform(0.01,0.05)
gfc(j)	Uniform(1000,2000)	o(t)	Uniform(500000,900000)
dfc(i)	Uniform(500,3000)	β	Uniform(1000,10000)
pfc(j)	Uniform(500,2000)	lc	Uniform(0.001,0.003)
mfc(j)	Uniform(200,330)	D(j, t, t′)	Uniform(29793.764,29793.764)
pri(t)	Uniform(500,1500)	Pr(t, t′)	Uniform(3300.8393,3300.8393)
Tcap(i)	Uniform(200000,1000000)	$Emi(k)$	Uniform(230,240)
F	1	U	1
τ_i	0.3	ρ_s	Reported in Table 5

The deterministic and stochastic formulations were solved using the same numerical data in order to evaluate the impact of uncertainty on strategic redesign decisions. The resulting Pareto-optimal solutions for both formulations are reported in Tables 3 and 4, while their corresponding Pareto fronts are illustrated in Figure 2.

Table 3. Pareto-optimal solutions obtained for the deterministic model using AUGMECON method (billion USD)

Point	ε	Value of the first objective function	Value of the second objective function
1	0.1621645	16.4073	162.1645
2	0.1644551	11.9096	164.4551
3	0.1667456	11.3549	166.7456
4	0.1690362	10.9994	169.0362
5	0.1713268	10.7215	171.3268
6	0.1736173	10.4893	173.6173
7	0.1759079	10.3286	175.9079
8	0.1781985	10.2119	178.1985
9	0.1804891	10.1463	180.4891
10	0.1827796	10.1339	182.4561

Table 4. Pareto-optimal solutions obtained for the stochastic model using the AUGMECON method (billion USD)

Point	ε	Value of the first objective function	Value of the second objective function
1	0.1161396	19.9819	161.3960
2	0.1639471	14.6698	163.9471
3	0.1664983	11.9206	166.4983
4	0.1690495	11.2114	169.0495
5	0.1716007	10.8559	171.6007
6	0.1741519	10.5794	174.1519
7	0.1767031	10.3708	176.7031
8	0.1792542	10.2305	179.2542
9	0.1818054	10.1493	181.8054
10	0.1843566	10.1347	183.8413

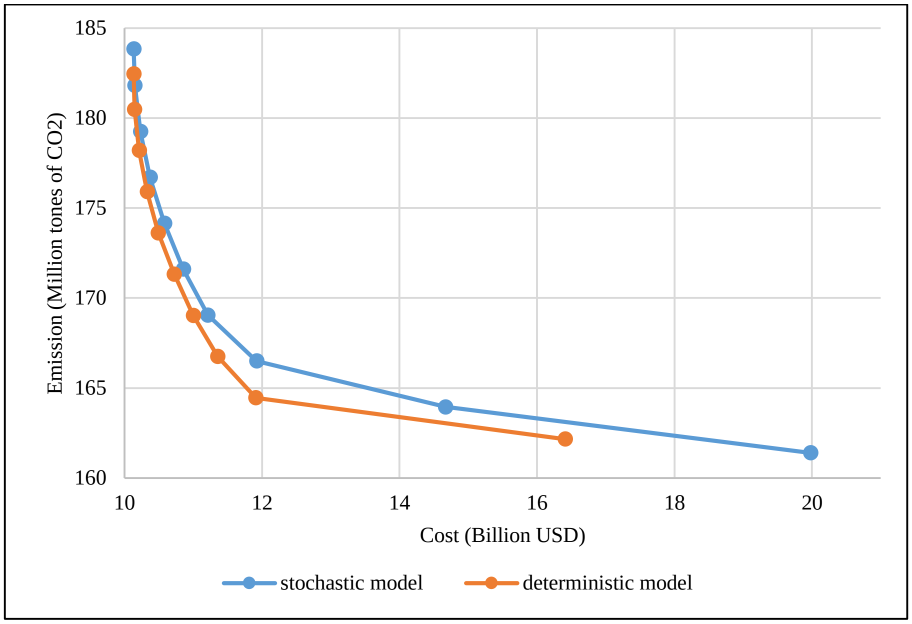

Figure 2. Pareto fronts obtained for the deterministic and stochastic formulations using the AUGMECON method

The comparison of the two Pareto fronts demonstrates that incorporating uncertainty substantially affects the trade-off between economic and environmental objectives. While the deterministic formulation provides optimal solutions for a single expected operating condition, the stochastic formulation identifies solutions that remain feasible across multiple future scenarios. Consequently, the efficient frontier shifts after uncertainty is incorporated, reflecting the additional flexibility required to hedge against uncertain demand and electricity price fluctuations.

For the economic objective, the maximum network cost increases from 16.41 to 19.98 billion USD, whereas the minimum cost changes only marginally from 10.1339 to 10.1347 billion USD. This behavior indicates that accounting for uncertainty primarily affects infrastructure configurations associated with high-cost operating conditions while preserving the efficiency of low-cost solutions. A similar pattern is observed for greenhouse gas emissions. The stochastic model achieves a slightly lower minimum emission level and simultaneously reduces the upper bound of emissions compared with the deterministic formulation. These observations indicate that explicitly considering uncertainty modifies the shape of the Pareto frontier rather than simply shifting objective values.

Overall, the results demonstrate that deterministic planning may underestimate the long-term consequences of uncertainty, particularly for infrastructure investment decisions. In contrast, the proposed stochastic formulation identifies redesign strategies that provide a better balance between economic efficiency and environmental performance over a range of plausible future operating conditions.

The optimal values of the decision variables provide further insight into the redesign strategy identified by the proposed model. The strategic decisions indicate that only limited structural modifications are required over the planning horizon. Specifically, two new microgrids are installed, at node 4 during the first planning period ($z_{41} = 1$) and at node 5 during the second planning period ($z_{52} = 1$). In addition, one distributed generation unit is installed at node 4 in the first planning period ($m_{341} = 1$), while another distributed generation unit at node 5 is decommissioned during the second planning period ($m_{252} = 1$). Furthermore, one conventional generator at node 6 is decommissioned during the second planning period ($n_{262} = 1$). These decisions indicate that the proposed framework improves network performance through targeted infrastructure reconfiguration rather than extensive network expansion. The operational decision variables also exhibit a selective resource allocation strategy. Electricity transmission through the high-voltage network is concentrated on a limited number of transmission paths, whereas electricity distribution through the local distribution network supplies all demand nodes according to their requirements. The distributed generation results indicate that DG units at nodes 1-3 remain active throughout the planning horizon, the DG at node 4 is introduced in the first planning period, the DG at node 5 is removed in the second planning period, and no generation is assigned to the DG at node 6. Similarly, the generation capacity results show that generators located at nodes 1-3 remain active in both planning periods, generators at nodes 4 and 5 are not utilized, and the generator at node 6 is decommissioned during the second planning period. Finally, the shortage variable remains equal to zero in the optimal solution, confirming that all electricity demand is satisfied without unmet load under the considered planning scenarios.

For the proposed numerical example, EVPI= $z_S - z_P$=0.00174111 and VSS= $z_D - z_S$= 0.4667. Although the EVPI value is relatively small, it confirms that uncertainty imposes a measurable economic cost on the redesign problem. More importantly, the VSS value indicates that ignoring uncertainty and relying solely on expected parameter values would increase the expected system cost by approximately 0.47 billion USD. This considerable difference demonstrates that explicitly incorporating uncertainty into the redesign model leads to substantially more reliable and economically efficient planning decisions.

5.2. Sensitivity Analysis

Following, a sensitivity analysis was conducted to further investigate the influence of demand and electricity selling price variations. The analysis was performed using the same nine demand-price combinations considered in the stochastic model, and the corresponding objective function values are summarized in Table 5.

Table 5. Sensitivity analysis results for the proposed stochastic model (billion USD)

scenario	changes	objective function (cost)	probability	price	demand
1	+0.12	11.404	0.075	3000.763	32773.140
2	−0.12	8.908056	0.075	3630.893	26814.394
3	−0.02	9.897853	0.1	3630.893	29793.767
4	+0.02	10.3672	0.1	3000.763	29793.764
5 (base scenario)	0.00	10.1336	0.3	3300.8393	29793.764
6	+0.1	11. 1470	0.1	3300.8393	32773.140
7	−0.1	9.120177	0.1	3300.8393	26814.394
8	+0.07	10.8876	0.075	3630.893	32773.140
9	−0.07	9.330344	0.075	3000.763	26814.394
10	0.03	10.1335	--	--	--

The scenario analysis confirms that demand uncertainty has a greater influence on the network cost than fluctuations in electricity selling prices. As expected, higher electricity demand requires additional generation and power transmission, resulting in higher operating costs. Conversely, lower demand reduces the required generation capacity and consequently decreases the total network cost. Variations in electricity selling prices also affect the economic objective; however, their impact is less pronounced because the redesign decisions are primarily driven by infrastructure configuration rather than short-term market fluctuations.

An important observation is that the expected stochastic solution remains very close to the deterministic base-case solution while maintaining feasibility under all considered scenarios. This demonstrates that the proposed two-stage stochastic programming model successfully balances long-term investment decisions with uncertain operational conditions and provides solutions that are considerably more robust than those obtained using deterministic optimization alone.

To further evaluate the robustness of the proposed framework, a sensitivity analysis was performed by varying the parameters that have the greatest influence on redesign decisions. The selected parameters include transmission loss coefficient, generation cost, electricity demand, electricity selling price, and transmission distance, as summarized in Table 6.

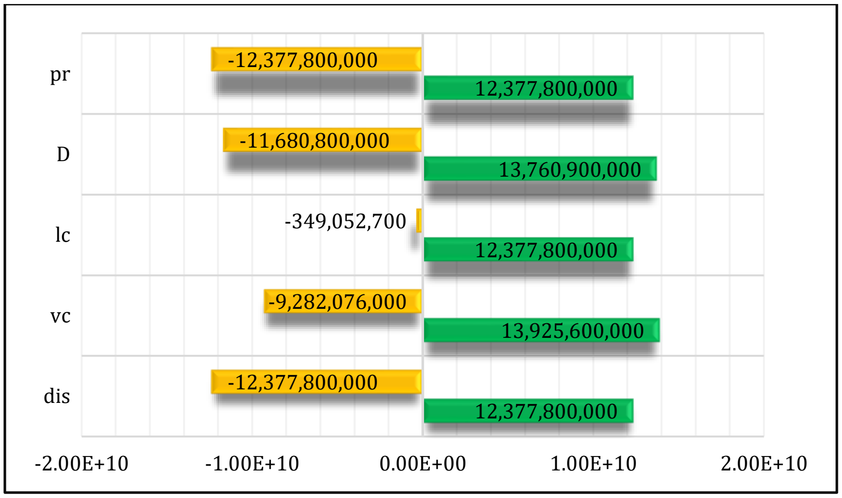

Figure 3. Tornado diagram of the objective function values for different demand–price scenarios and the expected stochastic solution

Table 6. Parameters considered in the sensitivity analysis

Row	Factors Influencing the Mathematical Model	Measuring Unit
1	$dis(i,j)$	percent
2	$vc(k,t,t')$	percent
3	lc	percent
4	$D(j,t,t')$	percent
5	$pr(t,t')$	percent

The relative influence of these parameters on the economic objective was evaluated using Tornado analysis. The resulting Tornado chart is presented in Figure 4, which clearly ranks the parameters according to their impact on the total network cost.

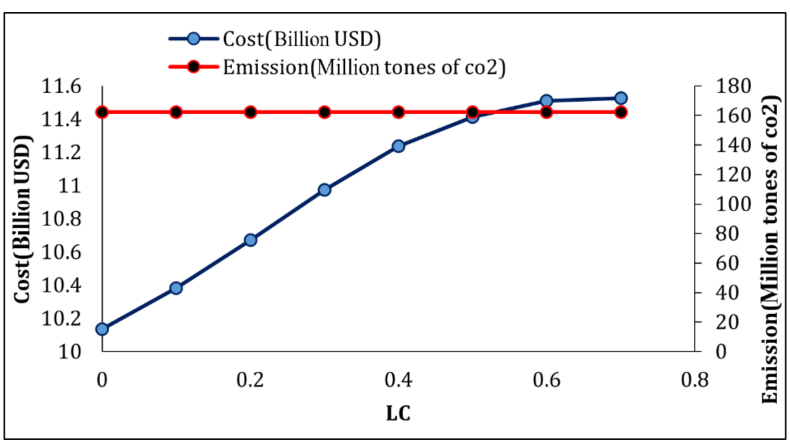

Figure 4. Tornado chart showing the relative influence of key model parameters on the economic objective

The Tornado analysis indicates that the transmission and distribution loss coefficient is the dominant factor affecting the total system cost, followed by generation cost and electricity demand. By contrast, electricity selling price and transmission distance exhibit comparatively smaller effects within the investigated ranges. These findings suggest that improving transmission efficiency provides greater economic benefits than merely adjusting pricing policies or modifying network topology.

Because the three most influential parameters account for the majority of the observed variation, a detailed sensitivity analysis was performed only for these parameters. The corresponding results are illustrated in Figures 5-7.

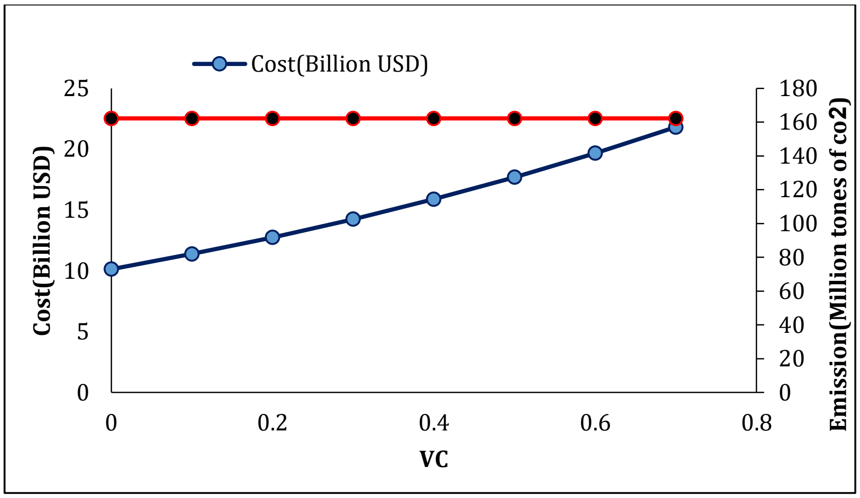

Figure 5. Sensitivity analysis of the transmission and distribution loss coefficient

The results show that increasing the transmission loss coefficient leads to a continuous increase in the total system cost because additional electricity generation is required to compensate for transmission losses. The environmental objective remains nearly unchanged throughout the investigated range, indicating that the generation portfolio remains largely unaffected by transmission losses.

This result indicates that improving transmission efficiency is economically more effective than expanding generation capacity alone. Therefore, investments in transmission infrastructure and loss reduction technologies can provide substantial long-term economic benefits while maintaining environmental performance.

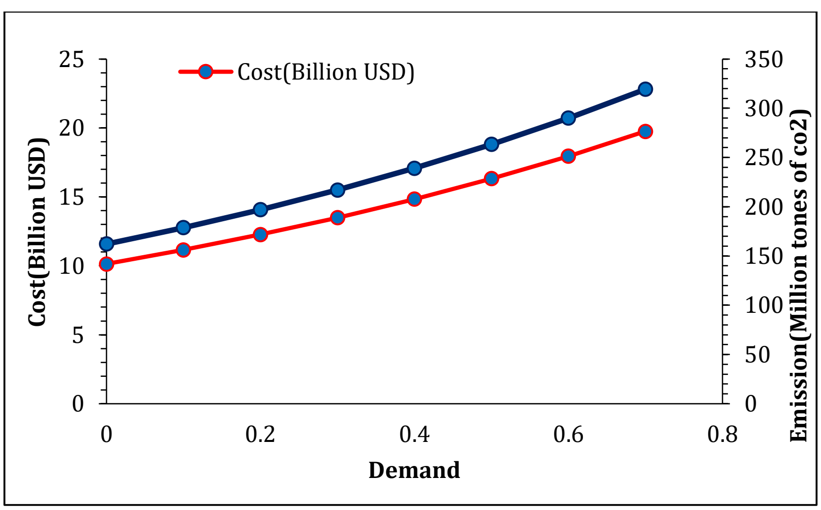

Figure 6. Sensitivity analysis of generation cost

As expected, the total network cost increases almost linearly with higher generation costs, whereas greenhouse gas emissions remain practically unchanged. This behavior indicates that production cost mainly affects operational expenditures without significantly altering generation technologies selected by the optimization model.

The nearly linear response suggests that generation cost mainly influences operational expenditures rather than strategic technology selection. Consequently, policies aimed at improving generation efficiency or reducing production costs can directly enhance the economic performance of the redesigned network.

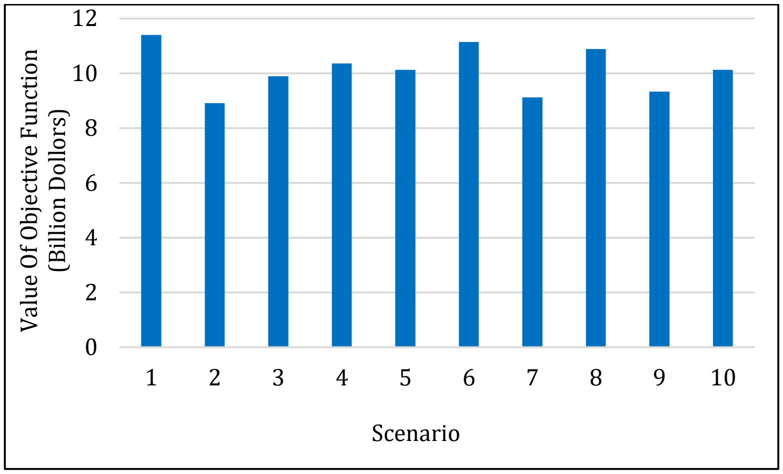

Figure 7. Sensitivity analysis of electricity demand

Unlike the previous two parameters, increasing electricity demand simultaneously increases both objective functions. Higher demand requires additional electricity production, resulting in increased operating costs together with higher greenhouse gas emissions. This confirms that future demand growth is one of the principal drivers of both economic and environmental performance in electricity supply chain redesign.

The simultaneous increase in both objectives indicates that future demand growth directly intensifies the economic-environmental trade-off. This finding highlights the importance of demand-side management and energy efficiency programs in supporting sustainable electricity network planning.

The numerical experiments demonstrate that uncertainty significantly influences long-term redesign decisions and should therefore be explicitly incorporated into strategic planning models. The stochastic formulation consistently generates solutions that remain economically competitive while providing substantially greater robustness against future operating conditions. Furthermore, the sensitivity analysis identifies transmission efficiency, generation cost, and electricity demand as the primary factors influencing network performance. These findings suggest that investments aimed at reducing transmission losses and improving energy efficiency may produce greater long-term benefits than simply expanding generation capacity.

The proposed framework also provides practical support for strategic infrastructure planning by simultaneously considering generator installation and retirement, distributed generation deployment, electricity pricing, and capacity allocation within a unified optimization framework. Rather than optimizing these decisions independently, the model identifies coordinated redesign strategies that balance economic performance and environmental sustainability under uncertainty. From a managerial perspective, the positive values obtained for EVPI and VSS further demonstrate that explicitly accounting for uncertainty can substantially reduce the expected long-term cost of network redesign. Consequently, the proposed stochastic optimization approach offers a reliable decision-support tool for electricity utilities and infrastructure planners seeking to improve network resilience while facilitating the transition toward more sustainable and decentralized energy systems.

Detailed values of the first-stage and second-stage decision variables obtained for each scenario are reported in Appendix A.

6. Conclusion

This study addressed the redesign of sustainable electricity supply chain networks by proposing a scenario-based two-stage stochastic optimization model that simultaneously considers strategic redesign decisions and operational planning under uncertainty. Unlike conventional electricity network design models that primarily focus on expansion planning, the proposed framework explicitly incorporates redesign decisions, including the installation and closure of conventional generators and distributed generation units, together with electricity generation, capacity allocation, pricing, and power distribution decisions. The model minimizes both the total network cost and greenhouse gas emissions while accounting for uncertainty in electricity demand and market selling prices.

The computational results demonstrate that explicitly incorporating uncertainty into the planning process leads to more reliable redesign decisions than deterministic planning. Comparison of the deterministic and stochastic Pareto fronts shows that uncertainty changes the attainable trade-off between economic and environmental objectives, confirming that deterministic solutions may underestimate the cost of operating under uncertain conditions. The scenario analysis further indicates that variations in demand have a stronger impact on network performance than electricity price fluctuations, highlighting the importance of demand uncertainty in long-term electricity infrastructure planning. In addition, the sensitivity analysis identifies the transmission loss coefficient, variable generation cost, and electricity demand as the most influential parameters affecting the economic performance of the network. These findings provide useful insights into the parameters that deserve particular attention during strategic planning and infrastructure investment.

The calculated EVPI and VSS values further demonstrate the practical value of stochastic programming. The positive EVPI indicates the economic value of obtaining more accurate information about future uncertain parameters, whereas the VSS confirms that explicitly modeling uncertainty results in lower expected costs than relying on deterministic approximations. These findings justify the use of stochastic optimization for redesign problems in smart electricity networks operating under uncertain conditions.

The proposed framework also provides insights into the interactions between strategic redesign and operational decisions in sustainable electricity supply chains. The results show that jointly determining generator installation and retirement, distributed generation deployment, electricity generation, pricing, and capacity allocation can improve the balance between economic and environmental objectives under uncertainty. These findings demonstrate the potential advantages of integrating redesign and operational planning within a unified stochastic optimization framework for electricity supply chain networks.

Despite these contributions, the present study has several limitations that provide opportunities for future research. First, uncertainty is represented only through electricity demand and selling prices, whereas other important sources of uncertainty, such as renewable energy generation, equipment failures, and electricity market disruptions, are not explicitly considered. Second, the proposed scenario-based stochastic model adopts a risk-neutral decision-making perspective and therefore does not explicitly account for solution robustness under highly uncertain operating conditions. Finally, the model focuses on economic and environmental objectives without incorporating social sustainability indicators.

Future research may address these limitations by considering additional sources of uncertainty and developing more comprehensive uncertainty-handling approaches. In particular, scenario-based robust optimization frameworks, such as the Mulvey robust optimization approach (Mulvey & Ruszczyński, 1995), or more recent scenario-based robust optimization models (Pourahmadi et al., 2023), as well as hybrid stochastic-robust formulations, could be employed to generate solutions that are less sensitive to scenario variations while improving solution robustness under uncertainty. Other promising research directions include integrating renewable energy storage technologies and blockchain-enabled energy trading mechanisms into electricity supply chain redesign models. Furthermore, extending the model to incorporate social sustainability objectives would provide a more comprehensive assessment of sustainable electricity supply chains. From the perspective of the Sustainable Development Goals, future research may further contribute to SDG 12 (Responsible Consumption and Production) by promoting more resource-efficient electricity systems and to SDG 8 (Decent Work and Economic Growth) by incorporating social and employment-related sustainability indicators into electricity supply chain redesign models.

Author Contributions

All authors contributed equally to the conceptualization of the article and writing of the original and subsequent drafts.

Data Availability Statement

Data available on request from the authors.

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Ethical considerations

The authors avoided data fabrication, falsification, and plagiarism, and any form of misconduct.

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Conflict of interest

The authors declare no conflict of interest.

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Appendix A. Optimal decision variable values

To improve the readability of the main manuscript, the complete values of the decision variables obtained from the stochastic optimization model are provided in this appendix. These variables correspond to the optimal first-stage redesign decisions and second-stage operational decisions under each scenario. They are reported for completeness and to facilitate the reproducibility of the numerical example.

Table A1. Optimal values of the decision variables for the minimum-cost solution under different scenarios

H1	LB ∗ SC1	LB ∗ SC2	LB ∗ SC3	LB ∗ SC4	LB ∗ SC5	LB ∗ SC6	LB ∗ SC7	LB ∗ SC8	LB ∗ SC9
x	813025.479	696585.334	774099.410	739004.372	774099.410	851613.485	696585.334	851613.485	664983.265
y	32020.898	0.00	0.00	29041.522	0.00	0.00	0.00	0.00	26062.145
g	1842.079	916.522	916.522	1842.079	916.522	916.522	916.522	916.522	1842.079
e	20705940	20715970	20715970	20705940	20715970	2071597	20715970	20715970	20705940
q	6999.522	6238.244	6238.244	6999.522	6238.244	6238.244	6238.244	6238.244	6999.522
δ	543191.553	543191.553	543191.553	543191.553	543191.553	543191.553	543191.553	543191.553	543191.553
θ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table A2. Optimal values of the decision variables for the minimum-emission solution under different scenarios

H2	LB ∗ SC1	LB ∗ SC2	LB ∗ SC3	LB ∗ SC4	LB ∗ SC5	LB ∗ SC6	LB ∗ SC7	LB ∗ SC8	LB ∗ SC9
x	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
y	771854.306	628844.239	700349.272	700349.272	700349.272	771854.306	628844.239	771854.306	628844.239
g	14701.064	14701.064	14701.064	14701.064	14701.064	14701.064	14701.064	14701.064	14701.064
e	18650320	18650320	18650320	18650320	18650320	18650320	18650320	18650320	18650320
q	7350.532	7350.532	7350.532	7350.532	7350.532	7350.532	7350.532	7350.532	7350.532
δ	543402.065	542118.201	543402.065	543402.065	543402.065	543402.065	542118.201	543402.065	542118.201
θ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00