Computers and Chemical Engineering 214 (2026) 109779

Contents lists available at ScienceDirect

Computers and Chemical Engineering

journal homepage: www.elsevier.com/locate/compchemeng

A multistage stochastic mixed integer optimization model for the design of a renewable fuel supply chain network under demand uncertainty

Mina Farajiamiri *, Jörn-Christian Meyer, Grit Walther

RWTH Aachen University Aachen, NRW, Germany

ARTICLE INFO

Keywords:
Decision support systems
Multi-stage stochastic programming
Renewable fuel supply chain network design
Mixed integer linear programming
Demand uncertainty

ABSTRACT

Decarbonizing the hard-to-electrify transportation sector hinges on adopting renewable fuels. This transition to renewable fuels requires robust planning tools that can account for long-term demand uncertainty and evolving supply chain structures. This study develops a multi-stage stochastic mixed-integer linear program for the design of renewable fuel supply chain networks under uncertain demand. Unlike existing approaches that rely on deterministic or two-stage formulations, the proposed model captures sequential decision-making over time and enables adaptive responses to uncertainty. The model features a flexible multi-period, multi-stage framework supporting a wide range of products and feedstocks, considering seasonal and regional supply variability.

A data-driven scenario generation and reduction framework is integrated to construct a tractable yet representative scenario tree. The model is applied to a European case study spanning 2021–2060, incorporating multiple fuel pathways and import strategies, including both long-term contracts and spot market procurement.

The results shows the substantial economic advantage of our multi-stage approach. The stochastic model significantly outperforms deterministic planning, achieving a Relative Value of the Multi-Stage Stochastic Solution of 19.4% and an Expected Value of Perfect Information of 14.2%. Furthermore, the analysis demonstrates how the proposed model effectively balances strategic and tactical decisions under demand uncertainty. By accounting for sequential information updates, the framework reveals the interplay among technology costs, regional resource availability, and import strategies.

These findings underscore the value of dynamic decision-making while offering practical guidance for policymakers and industry stakeholders in planning future renewable fuel supply chains. Overall, the proposed adaptive framework functions as a robust decision-support tool, enabling cost-efficient and flexible decarbonization planning.

1. Introduction

The transportation sector is a major emitter of greenhouse gasses worldwide. In 2022, transport was responsible for 29% of the EU's greenhouse gas emissions (EEA, 2024). Decarbonization in heavy-duty vehicles, aviation, and maritime poses particular challenges. While electrification is gaining traction in passenger cars, these heavier segments will continue to use drop-in fuels for decades to come (IEA, IEA 2022). Consequently, a range of renewable fuels (e.g., Methanol (MeOH), Fischer–Tropsch fuels (FT-fuel), Hydrogen (H_2), Ammonia (NH_3), etc.) have increasingly been recognized as essential for reducing emissions, diversifying energy mixes, and enhancing energy security (Fasihi et al., 2017).

Scaling renewable fuels requires supply chain (SC) structures that can reliably link upstream resource availability (biomass, water, CO_2, renewable electricity) with downstream fuel demand under uncertain and dynamic conditions. SC design is complex, involving multiple feedstocks, diverse fuel types, and emerging technologies and facilities. Long-term planning must account for seasonal and fluctuating resource availability as well as evolving regulations, market conditions, and technological progress (IRENA, WTO 2024).

Additionally, in many regions, especially where renewable resources are limited but demand is high, international trade and imports become essential to secure an adequate feedstock supply and ensure consistent production (Galimova et al., 2023). Imports offer both additional supply and a hedge against uncertainty for RFSC. Two import options are particularly relevant: contracted imports via long-term agreements (stable volumes/prices, limited flexibility) and spot imports

* Corresponding author.
E-mail address: mina.amiri@om.rwth-aachen.de (M. Farajiamiri).

https://doi.org/10.1016/j.compchemeng.2026.109779
Received 22 March 2026; Received in revised form 12 June 2026; Accepted 26 June 2026
Available online 29 June 2026
0098-1354/© 2026 The Author(s). Published by Elsevier Ltd. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).

(short-notice procurement at higher cost to cover unexpected shortfalls). Modeling both is essential to capture the trade-off between supply security and flexibility, yet differentiated import strategies are largely missing in RFSC network design models.

A reliable fuel SC is essential for renewable fuels, yet multiple uncertainties hinder their deployment (Huang et al., 2014). Resource availability depends on seasonality, feedstock competition, and evolving potentials (Poudel et al., 2016). At the production stage, emerging technologies like electrolysis and direct air capture (DAC) face uncertain costs and scalability (Yue et al., 2014). On the demand side, shifting policies, efficiency gains, competition from electric vehicles, and changing consumer behavior make long-term demand highly unpredictable (IEA, 2021). These uncertainties are amplified by capital-intensive, long-lived infrastructure requiring multi-decade planning (Xie and Huang, 2018; Zarei et al., 2022). Deterministic models, while common, risk generating infeasible or suboptimal solutions when reality diverges from fixed assumptions.

Stochastic programming represents the frontier of decision-making for RFSC under uncertainty, providing the mathematical rigor needed to navigate a future defined by variability. It embeds uncertain parameters directly into the network design problem and optimizes decisions with respect to a set of plausible future realizations, thereby balancing cost, feasibility, and robustness across scenarios. It enables planners to distinguish long-lived strategic investments from adaptive operational responses, which is essential in RFSCs where infrastructure choices are capital-intensive and difficult to reverse. Common formulations include two-stage stochastic programming (TSSP), which couples upfront investment decisions with recourse actions after uncertainty is realized; multi-stage stochastic programming (MSSP), which captures the sequential revelation of information and repeated decision-making over time (Birge and Louveaux, 2011).

Demand is a key driver of SC design and performance (Yu et al., 2020), and accurate forecasting is essential for planning renewable fuel supply chains (RFSC). However, demand for renewable fuels is highly volatile due to diverse and sometimes conflicting projections, evolving policies, shifting economic and consumption patterns, market competition, uncertain social acceptance, and the growing adoption of hybrid and electric vehicles (Moustakas et al., 2020). These factors make demand forecasting challenging, making demand uncertainty one of the main sources of complexity in RFSC design and operation.

Despite the growing body of research on RFSC, three critical limitations remain. First, most studies rely on deterministic or TSSP that restrict the ability to model sequential, adaptive decisions over long planning horizons. Second, uncertainty modeling predominantly focuses on resources or price fluctuations, while long-term demand uncertainty for renewable fuels remains insufficiently addressed. Third, existing models rarely capture differentiated import strategies, such as long-term contracts and spot procurement, within a dynamic network expansion framework. As a result, current approaches provide limited insight into how infrastructure and sourcing decisions should evolve under uncertain demand pathways.

This paper aims to support the advancement of renewable fuels by developing an optimization-based framework for the design and analysis of RFSCs. To adequately represent these systems, the model must capture key structural and temporal requirements, including long-term demand uncertainty, seasonal variability in renewable resource availability, and the multi-period nature of investment decisions. The RFSC is formulated as a flexible network integrating multiple production, transportation, and storage technologies, while explicitly accounting for alternative import strategies (contracted and spot imports) to enhance long-term supply flexibility.

To address these requirements, we develop a multistage stochastic mixed-integer linear programming framework that links strategic investment and tactical operational decisions across multiple periods, enabling adaptive planning under sequentially revealed demand uncertainty. Demand scenarios are generated using an autoregressive process and reduced via a forward selection heuristic to ensure computational tractability. The framework is applied to an EU-wide case study, demonstrating how evolving demand information influences technology deployment, infrastructure expansion, and import strategies. By explicitly modeling adaptive decision-making under uncertainty, the proposed approach advances the literature on stochastic energy system planning and RFSC design while minimizing total system cost and providing transparent insights into long-term infrastructure and operational strategies.

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature. Section 3 introduces the problem context, outlines the specific characteristics of RFSCs, and presents the MSSP model along with the scenario construction approach. Section 4 describes the EU case study. Section 5 presents the numerical results and discussion. Finally, Section 6 concludes the paper and highlights directions for future research.

2. Literature review

This review examines key aspects of RFSC design, with a particular focus on how uncertainties influence their planning and operation, and discusses relevant applications of stochastic programming in this domain.

2.1. Complexities in renewable fuel supply chain design

SC optimization has been widely studied and applied in various industries. Matinrad et al. (2013) describe an SC as a cooperative network structured to meet consumer demands, highlighting the popularity of multi-echelon, multi-period SCs and their application across numerous industrial contexts. Pourhejazy et al. (Pourhejazy and Kwon, 2016) emphasize the growing focus on sustainability in modern SCs and confirm the suitability of mathematical models for capturing the complexity of SC attributes. Mathematical models for designing an SC may differ based on their network structure, planning horizon, capacity, production, inventory decisions, and multiple or single commodities (Melo et al., 2009).

The transition away from fossil fuels due to environmental concerns is driving the research on RFSCs, with papers often focusing on single resources or products (Yue et al., 2014; Čuček et al., 2014; Malladi and Sowlati, 2018; Zandi Atashbar et al., 2018). Fewer studies examine SCs with multiple fuels or technologies (Wolff et al., 2023). Much of the existing work is limited to single-pathway analyzes and does not account for flexible SCs or integrated resources and production pathways. While some research explores multiple technological pathways for renewable liquid fuels, it often focuses on energy-system-level analysis rather than detailed SC modeling (Albrecht et al., 2017; Albrecht and Nguyen, 2020; Quarton and Samsatli, 2020).

Temporal and structural complexity further shape RFSCs. Some studies do consider seasonal variability by incorporating renewable energy storage (Liu et al., 2017; Quddus et al., 2018; Fattahi and Govindan, 2018). The design of RFSCs also demands solutions to handle complexity arising from long planning horizons or high time resolution; methods like time decomposition have been proposed to manage many decision variables (Quarton and Samsatli, 2020; Lara et al., 2018). Reflecting a growing awareness of dynamic conditions, recent research has moved toward multi-period frameworks (Čuček et al., 2014; Wolff et al., 2023; Lim and Ouyang, 2016; Xie et al., 2014; Samsatli and Samsatli, 2018; Hombach and Walther, 2015; Hombach et al., 2016). Recent studies have also proposed integrated multi-objective and decision-support frameworks for renewable energy transportation and supply chain planning to evaluate trade-offs among cost, environmental impact, and transportation risk across alternative energy carriers and pathways (Iseri et al., 2025a, 2025b). Furthermore, different import strategies remain underexplored. Most models treat international trade simplistically, overlooking the strategic role of

long-term contracts and flexible spot purchases in balancing EU demand with limited domestic supply (Maurice Vos, 2020; Nichol et al., 2023; Shin et al., 2025).

2.2. Approaches to uncertainty in RFSCs

Uncertainty is a defining characteristic of RFSCs. Key uncertainties addressed in the literature include feedstock supply (Huang et al., 2014; Poudel et al., 2018; Guo et al., 2022; Memişoğlu and Üster, 2021; Castillo-Villar et al., 2017), fuel demand (Xie and Huang, 2018; Osmani and Zhang, 2013; Asadi et al., 2018; Gonela et al., 2015; Osmani and Zhang, 2017; Kalhor et al., 2022), and SC costs and prices (Gonela et al., 2015; Zhang and Osmani, 2015; Osmani and Zhang, 2014; Cobuloglu and Büyüktahtakın, 2017). Additionally, some research includes disruption risks in biofuel SC planning, incorporating the probability of failures in facilities or transportation (Poudel et al., 2016; Marufuzzaman et al., 2014; Marufuzzaman and Ekşioğlu, 2017). Depending on data availability, different approaches are employed (Pishvaee et al., 2020). Epistemic uncertainty arises from incomplete credibility of data, often modeled via fuzzy or possibilistic programming (Babazadeh et al., 2017; Ebadi Torkayesh et al., 2024; Hendiani and Walther, 2023). Deep uncertainty, where only parameter bounds are known, is addressed by robust optimization (Kalhor et al., 2022; Hombach et al., 2018; Delkhosh and Sadjadi, 2020; Ghelichi et al., 2018; Bairamzadeh et al., 2018). Randomness, based on reliable historical data, allows the use of stochastic programming methods such as chance-constrained, two-stage, or multi-stage models (Zarei et al., 2022; Memişoğlu and Üster, 2021; Aboytes-Ojeda et al., 2019; O'Neill et al., 2022; Li et al., 2022).

TSSP has been widely used for RFSC network design, typically modeling first-stage infrastructure investments (e.g., facilities) followed by second-stage operational recourse once uncertainty is realized (Osmani and Zhang, 2013; Gonela et al., 2015; Li and Hu, 2014; Sun et al., 2018). Multi-period extensions also incorporate uncertainty and seasonal feedstock variability (Huang et al., 2014; Poudel et al., 2016; Quddus et al., 2018, 2017). However, most TSSP formulations assume that uncertainty is revealed all at once, which oversimplifies how information unfolds over time in practice (Govindan et al., 2017). While this assumption can be acceptable for short-term planning, it becomes particularly limiting in multi-decade RFSC settings where capital-intensive investments (e.g., refineries, pipelines) lock in decisions for many years, and sequential decision-making is essential.

MSSP introduced by Birge et al. (Quddus et al., 2017) explicitly models the gradual revelation of uncertainty over time, yet remains underexplored for RFSCs. This gap is significant because RFSCs often need periodic adjustments to capacity, resource allocation, and tactical operations as new data emerge. In MSSP, uncertain parameters are generally modeled through discrete scenarios generated from historical data, enabling decisions to be updated at each stage as information unfolds (Xie and Huang, 2018; Fattahi and Govindan, 2018; Fattahi et al., 2017; Nickel et al., 2012; Fattahi et al., 2018).

Studies applying MSSP to complex planning problems under uncertainty across domains such as SCs (Govindan et al., 2017; Birge and Louveaux, 2011; Fattahi et al., 2017; Nickel et al., 2012; Fattahi et al., 2018; Goh et al., 2007), manufacturing networks (Aboytes-Ojeda et al., 2019; Goh et al., 2007; Felfel et al., 2015; Pimentel et al., 2013; Huang and Ahmed, 2009), water management (Ahmed et al., 2003; Hu and Hu, 2018; Zhang et al., 2019; Zhou et al., 2013), energy systems (Li et al., 2006; Wang and De Neufville, 2004; Kim and Lee, 2023; Wang et al., 2023; Hafiz et al., 2019), reverse logistics (Azizi and Hu, 2021), and relief distribution (Hu et al., 2019). These works demonstrate MSSP's flexibility in addressing diverse uncertainties, ranging from biomass supply and demand fluctuations to costs, prices, and capacity variations, using scenario trees, reduction techniques, decomposition, and heuristics. Many adopt multi-product, multi-resource, and multi-stage structures with temporal resolutions from seasonal to even minute-level decisions, highlighting MSSP's ability to capture sequential decision-making across scales.

However, despite its successful use in related fields, applications to RFSCs remain scarce. Existing studies largely favor two-stage models, overlooking the gradual evolution of uncertainty and the need for periodic adjustments in investment, production, transport, and storage. Table 1 presents an overview of related studies on RFSC optimization. Building on the prior advances in literature, our study positions MSSP as a robust framework for explicitly modeling the dynamic, uncertain nature of RFSCs, enabling more realistic long-term planning.

2.3. Research gaps and contribution

The reviewed literature highlights three key shortcomings that extend beyond the general challenges of uncertainty modeling and practical applicability:

1. Overreliance on deterministic, two-stage, or robust optimization approaches, which fail to capture the sequential unfolding of uncertainty and the adaptive nature of real-world decision-making.
2. Simplified temporal and scenario representations, often limited to annual resolutions, which overlook seasonal dynamics and operational flexibility. Many studies also remain highly localized, reducing their scalability and applicability to continental or long-term planning horizons.
3. Limited scope in resource and technology coverage, with most models focusing on a single feedstock or fuel while neglecting the diversity of storage solutions and transportation modes. This restricts the ability to identify complementarities and synergies across renewable resources and technologies.

To sum up, RFSCs are inherently complex and dynamic systems, shaped by long-term uncertainty, temporal variability, and the interaction of multiple technologies, resources, and decision layers. In this study, we address two main research questions. First, from a modeling perspective, we develop a flexible multistage stochastic framework for RFSC design and address the following key questions: 1a) How can the design of an RFSC be formulated to capture multiple resources, fuels, technologies, and time periods within a unified and flexible structure? 1b) How can long-term demand uncertainty be explicitly modeled to enable adaptive decision-making across strategic and operational levels? 1c) How can large-scale, multi-period stochastic problems remain computationally tractable while preserving decision-relevant variability?

Second, we investigate the structural and operational implications of uncertainty within an EU-wide RFSC case study. In this context, the analysis focuses on: 2a) How does uncertainty influence total system cost and the economic value of adaptive decision-making? 2b) How are infrastructure investments, technology choices, and resource allocations shaped over time under different demand realizations? 2c) What role do contracted and spot import strategies play in ensuring flexibility, and how does the balance between domestic production and imports evolve under uncertainty? 2d) What key design levers drive robust and cost-efficient pathways for renewable fuel deployment? These questions define the central focus of this work and guide the evaluation of the proposed framework.

To overcome the limitations identified in the literature and answer research questions, this study develops an MSSP framework explicitly tailored to RFSCs. First, it addresses the overreliance on deterministic, two-stage, or robust approaches by capturing the sequential unfolding of uncertainty, thereby enabling adaptive adjustments of strategic and operational decisions across multiple periods. Second, it overcomes simplified temporal and scenario structures by linking long-term infrastructure investments with seasonal operational decisions, supported by an autoregressive scenario generation method and a forward selection reduction algorithm that preserves variability while ensuring

Table 1
Overview of related renewable fuel studies.

Study	Resource diversity	Multi-modal storage	Multi-modal transportation	Seasonality	Fuel types	Modeling framework	Demand uncertainty	Case study
(Azizi and Hu, 2021)	×	×			MeOH	Deterministic	_	_
(Hu et al., 2019)	×		×	×	F T-fuel	Deterministic	_	EU+UK
(Iseri et al., 2025)	×	×	×	×	H_2, MeOH, NH_3	Deterministic (Multi-Objective)	_	Germany
(Vo et al., 2025)	×	×	×	×	FT-fuel, H_2, MeOH	Deterministic	_	EU+UK
(Iseri et al., 2025)	×	×	×	×	H_2, MeOH, NH_3	Deterministic (AHP, Multi-Objective)	_	Germany
(Wolff et al., 2023)	×	×	×	×	H_2	Deterministic	_	EU
(Farajiamiri et al., 2023)	×			×	H_2	TSSP	×	UK
(Reuß et al., 2017)		×		×	H_2	TSSP	×	9 Regions
(Efthymiadou et al., 2025)				×	B io-fuel	TSSP		Michigan
(Kim et al., 2024)				×	B io-fuel	TSSP		Illinois
(O'Neill et al., 2022)			×	×	Bio-fuel	TSSP		South US
(Guo et al., 2022)				×	B io-fuel	TSSP		Texas
(Nur et al., 2021)				×	H_2	TSSP	×	UK
(Memişoğlu and Üster, 2021)	×				H_2	TSSP	×	New Jersey
(Nunes et al., 2015)	×	×		×	H_2	TSSP	×	UK
(Dayhim et al., 2014)	×			×	B io-fuel	TSSP	×	Iran
(Almansoori and Shah, 2012)	×		×	×	B io-fuel	TSSP	×	Wisconsin
(Ghelichi et al., 2018)			×	×	Bio-fuel	TSSP		California
Mitrai et al. (2026)	×				NH_3	MSSP		_
Shuai et al. (2024)	×	×	×	×	H_2	MSSP	×	Asia
(Zarei et al., 2022)		×	×	×	B io-fuel	MSSP	×	South Korea
(Xie and Huang, 2018)			×		Bio-fuel	MSSP	×	C arolina
(Fattahi and Govindan, 2018)	×	×	×	×	Bio-fuel	MSSP		Iran
This Study	×	×	×	×	H_2, MeOH, NH_3,FT-fuel	MSSP	×	E U+UK

computational tractability. Third, it broadens the scope of resource and technology coverage by incorporating multiple feedstocks, products, storage options, transportation modes, and differentiated import strategies, allowing the model to reveal trade-offs and complementarities across diverse pathways. The framework is demonstrated through a large-scale EU-wide case study, which validates its practical applicability and provides actionable insights into technology selection, infrastructure expansion, and the balance between domestic production and imports. By bridging methodological advances with empirical evidence, this work positions MSSP as a robust and scalable tool for realistic long-term planning of RFSCs. The main contributions of this paper are:

- A comprehensive and flexible SC formulation that captures the structural complexity of renewable fuel systems, including multiple feedstocks, fuels, production pathways, storage facilities, transportation modes, seasonal resource variability, and long-term planning requirements, and embeds both contracted and spot import options.
- An MSSP framework that explicitly models the sequential revelation of long-term renewable fuel-demand uncertainty and links strategic infrastructure investments with tactical decisions in a unified mixed-integer linear programming model.
- Implement and tailor an autoregressive demand scenario generation combined with the adoption of a forward-selection scenario reduction algorithm to build a compact, decision-relevant scenario tree that remains tractable for large-scale, multi-stage, multi-decade, multi-commodity RFSC.
- A real-world, long-term, large-scale EU-wide case study demonstrating the practical applicability and effectiveness of the proposed framework, quantifying the economic value of sequential decision-making and revealing adaptive pathways for renewable-fuel infrastructure deployment, import strategies, and resource allocation.

3. Methodology

In this section, we will shortly describe the underlying problem, planning decisions, the MSSP framework to deal with uncertainty, and the scenario construction approach.

3.1. Problem setting

RFSCs differ from conventional SCs due to several structural and operational characteristics. Production relies on capital-intensive, technology-specific conversion processes that couple renewable electricity and feedstock availability with fuel output. The network simultaneously accommodates multiple feedstocks and renewable fuel products, creating interdependencies between alternative production pathways. In addition, various production, storage, and transportation technologies coexist, each characterized by distinct cost structures, efficiencies, and capacity expansion requirements. The spatial dimension further increases complexity, as resource availability, infrastructure capacity, and demand levels vary across regions, resulting in significant local disparities. Temporal heterogeneity also plays a central role: infrastructure investments are long-lived and largely irreversible, requiring careful timing decisions over a multi-decade planning horizon. At the operational level, renewable resource availability exhibits seasonal variability, which affects production profiles and storage requirements. Moreover, renewable fuels can be sourced domestically or through international import strategies, including long-term contracts and spot market procurement. Finally, future fuel demand is highly

uncertain and evolves gradually, necessitating adaptive decisions across multiple planning stages. These structural characteristics collectively justify the MSSP framework adopted in this study.

We model RFSC as shown in Fig. 1. The SC considers all types of materials as resources ($m \in M$), including raw materials (biomass, CO_2, water, electricity), intermediates (N_2, H_2), and final products (FT-fuel, MeOH, NH_3, H_2). It also considers the origins of resources, such as onshore/offshore wind and solar energy ($o \in O$). The seasonal variability of feedstock availability is explicitly accounted for within our model. Multiple production technologies and pathways ($p \in P$) that transform resources are evaluated, including hydrogen (H_2) production through Alkaline (AEL) and Proton Exchange Membrane (PEM) electrolysis. FT-fuels and MeOH are produced via three main pathways: Biomass-to-Liquid (BtL), Power-to-Liquid (PtL), and Power-Biomass-to-Liquid (PBtL). NH_3 production via the Haber–Bosch process is also included. These production technologies operate at varying capacity levels, with anticipated reductions in investment and operation & maintenance (O&M) costs as the technologies mature. While disruptive technological breakthroughs may occur by 2060, the production pathways selected for this study represent the fundamental, thermodynamically proven chemical processes for synthesizing these fuels. Therefore, the research assumes that these foundational pathways will remain the dominant scalable routes in use throughout the time horizon considered, even as their specific underlying components undergo incremental innovation (Raya-Tapia et al., 2025). Transportation within the SC involves biomass, CO_2, H_2, and fuels. Transportation modes ($q \in Q$) primarily include trucks and pipelines, with pipelines requiring initial investments ($Q_{inv} \subset Q$) and considered for CO_2 and H_2. Different capacities for pipelines transporting H_2 and CO_2 are evaluated. Different storage methods ($l \in L$) are considered for fuels, H_2, and CO_2 captured via DAC. There are several regions in the planning area ($i \in I$), each with its own resource potential (R_{oits}) and demand ($D_{mits\chi}$). In this paper, the assumption is that the demands are uncertain and a discrete set of possible demand scenarios ($\chi \in X$) with associated probabilities (Pr_χ, $\sum_\chi Pr_\chi = 1$) is available. In this paper, we distinguish between two types of imports: contracted imports, secured through long-term agreements, and spot imports, utilized only when demand exceeds the supply from domestic production and contracted sources.

We use the time aggregation method (Samsatli et al., 2015) to reduce the number of periods in long-term planning. In this time decomposition approach, long-term investment and short-term operational decisions are modeled on distinct temporal scales. Specifically, we consider two planning levels: strategic time periods ($t \in T$), defined in our case study as decadal, and tactical time periods ($s \in S$), defined as four seasons per year in our case study. More generally, both the length of strategic periods and the number of seasonal divisions are adjustable parameters depending on the application. Each strategic period comprises n annual periods, which are further split into seasonal intervals. In our case, a decadal level is constructed by aggregating ($n = 10$) years into a representative year repeated multiple times. This aggregation approach substantially improves computational tractability for the large-scale multistage stochastic problem; however, it may suppress interannual variability and therefore cannot fully capture year-to-year fluctuations in renewable resource availability and demand evolution. Seasonal periods follow cyclical orders, meaning each season's inventory balance links to the preceding one.

As shown in Fig. 1 our decision-making framework distinguishes clearly between strategic and tactical decisions. Strategic decisions set the long-term framework of the SC. They typically span multiple decades and include selecting production technologies, determining facility locations and capacities, establishing import contracts, and configuring transport and storage infrastructure. Tactical decisions, however, are made on a seasonal basis within each decade. They include allocating resources, production decisions, the amount of storage, transportation, spot imports, and procuring feedstock. This hierarchical approach aims to strategically balance the trade-off between investment in excess capacities and reliance on costly spot imports, which characterizes stable fulfillment of renewable fuel demand under uncertainty.

3.2. Multi-stage stochastic mixed-integer linear formulation

Strategic decisions regarding long-term renewable fuel infrastructure, such as the location of refineries, pipeline capacity, and technology pathways, often involve high switching costs and are typically irreversible. Assuming perfect knowledge of future demand from the outset can lead to overcapacities (and thus underutilized or even stranded assets if demand falls short) or undercapacities (leading to reliance on costly imports from spot markets or unmet demand). To effectively address these risks, this paper utilizes an MSSP approach. MSSP is an optimization framework for sequential decision-making under uncertainty across multiple periods. Initially, strategic decisions are made before uncertainties are revealed, while tactical decisions adapt flexibly as information unfolds. Thus, tactical decisions serve as recourse actions. Later strategic decisions also act as recourse actions, reflecting prior decisions and evolving uncertainties. Therefore, aside from initial strategic choices, every subsequent decision incorporates updated information.

Fig. 2 schematically illustrates the MSSP structure according to the time horizon of our case study. Each strategic period begins with long-term decisions made under uncertainty, followed by tactical adjustments once new information becomes available. Subsequent strategic periods build on earlier decisions, allowing adaptation to evolving conditions while preserving non-anticipativity. This sequential design captures how long-term infrastructure planning interacts dynamically with short-term operational flexibility.

In this multi-stage framework, it is critical to distinguish between the timing of decisions and the realization of uncertainty. The sequence of information revelation and decision-making unfolds as follows:

Stage 0 and strategic decisions (Start of T1, 2021–2030): Before any future demand uncertainty is realized, the model must make initial strategic investment decisions (e.g., initial production, storage, pipeline, and RES investments). These are "here-and-now" decisions made under the expectation of all future scenarios.

Stage 1 and tactical decisions (During T1, 2021–2030): As the decade progresses, demand development sequentially unfold. Tactical decisions (such as spot imports, production and storage amounts, resource utilization) act as recourse actions. Crucially, these tactical decisions are made on a seasonal basis and respond to the demand information that has materialized up to that point, ensuring the model never anticipates unrevealed future seasonal data

Subsequent Stages (T2, T3, T4): At the beginning of the next decade, using the historical knowledge of the previous decade's realized demand path, the model decided on the next round of strategic investments. These investments must again be made before the new decade's specific demand developments are known. This sequential process of *uncertainty realization → tactical decisions → updated strategic decisions* continues.

The non-anticipativity constraints (see equations 20-29) rigorously enforce this logic by ensuring that strategic decisions made at stage t are identical for any scenarios that share the same historical demand realizations up to stage t-1. The model is never allowed to "look ahead" into

future, unrevealed branches of the scenario tree.

According to Dupacova et al. (Raya-Tapia et al., 2025), MSSP can be formulated in two ways. The first nests TSSP models and incorporates non-anticipativity implicitly through recursive evaluation of the objective function. The second, used in this paper, explicitly imposes non-anticipativity constraints, ensuring that decisions at each stage do not rely on information not yet revealed. Following this approach, we develop a multi-stage mixed-integer stochastic program.

The presented formulation represents the complete mathematical model used in this study. The framework distinguishes between two categories of decision variables. Strategic decision variables correspond to long-term investment decisions and include both integer and continuous variables. As shown in Fig. 1, strategic decisions related to production, transportation, and storage are modeled as integer variables defining the number of installed or expanded facilities and infrastructures in each period. In contrast, installed RES capacities and contracted import quantities are modeled as continuous strategic variables. Tactical decision variables are continuous variables representing operational and utilization decisions, including resource utilization, production rates, storage levels, transportation flows, and spot import quantities. Fig. 1 and the associated nomenclature table below provide an overview of the decision variables, parameters, and sets, as well as their relationships to the corresponding supply chain components, including resources, production, transportation, storage, and imports.

Nomenclature:

Sets		
I	Set of regions	$i, i' \in I$
$CI \subset I$	Set of locations of caverns	
M	Set of resources	$m \in M$
O	Set of resource origins	$o \in O$
T_0	Set of planning periods with the start period	$T_0 \sim \{0\} \cup T$
$T \subset T_0$	Set of planning periods	$t \in T$
S	Set of seasons, S is a cyclic order	$s \in S$
P	Set of production technologies with different capacities	$p \in P$
L	Set of storage technologies	$l \in L$
Q	Set of transportation technologies	$q \in Q$
$Q_{inv} \subset Q$	Set of transportation technologies with different capacities that require an investment	
$RE \subset O$	Set of renewable electricity sources	$r \in RE$
X	Set of uncertainty scenarios	$\chi \in X$
Demand/Probability parameter - Uncertain		
$D_{mits\chi}$	Demand for resource m in region i in period t in season s for scenario χ [*tonnes /season*]	
Pr_χ	Probability of occurrence of scenario χ, $\left(\sum_\chi Pr_\chi = 1\right)$	
System parameters - Deterministic		
Θ_{ir}	Max allowable installation capacity for renewable electricity source r in region i [*MW*]	
R_{oits}	Potential of resource origin o at region i in period t in season s [*tonnes /season*], [*MWh /season*]	
ϑ_{isr}	Capacity factor of renewable electricity source r in region i and season s (EEA, 2024)	
υ_{mt}	Max amount of allowed resource m imported in period t	
α_{mp}	Rate of conversion of resource m by production technology p [*tonnes /tonnes*], [*MWh /tonnes*]	
β_{om}	1, if resource m is available from origin o; 0 otherwise	
K_p^{prod}	Production capacity of technology p [*tonnes /hour*]	
K_l^{stor}	Storage capacity of technology l per season [*tonnes /season*]	
K_q^{tran}	Transport capacity of technology q [*tonnes /hour*]	
A_{lm}	Resource m storable in technology l	
B_{qm}	Resources m transportable by technology q	
$d_{ii'}$	Distance between region i, i' [*km*]	
$B_{ii'}^{truck}$	Region pairs (i, i') that allow transportation via trucks	
$B_{ii'}^{pipe}$	Region pairs (i, i') that allow transportation via pipelines	
n	Years in a strategic time period	
H	Hours per season	
H'	Operating hours per season	

(*continued on next column*)

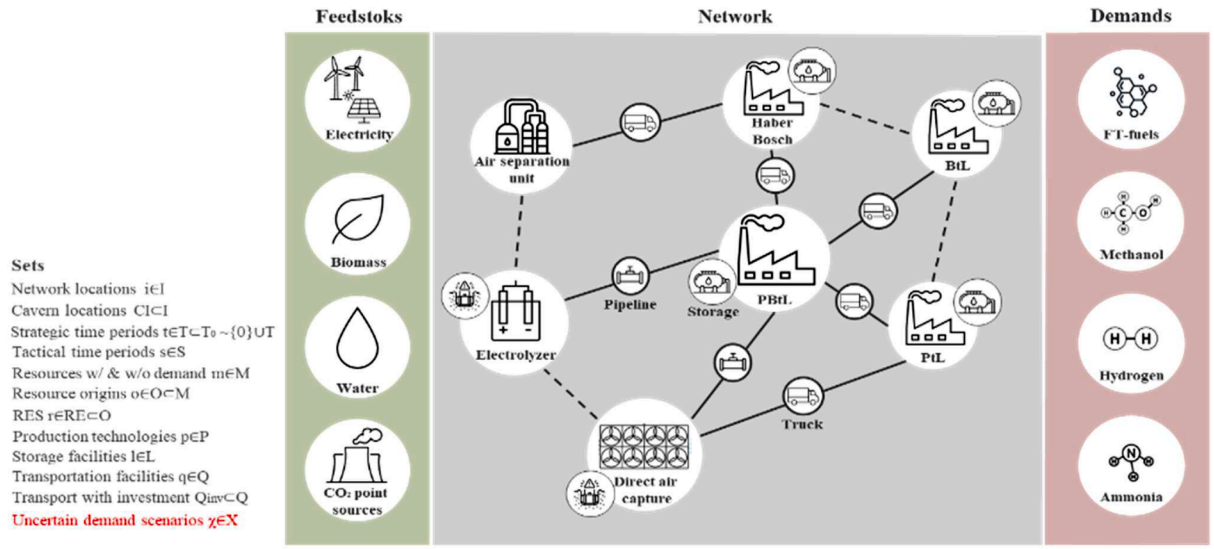
(*continued*)

Cost-related parameters - Deterministic	
τ	Rate of discounting [1 /*year*]
ζ_t^{sp}	Discount factor associated with strategic period t (EEA, 2024)
ζ_t^{yp}	Annual discount factor for period t (EEA, 2024)
f_p^{prod}	Investment cost for production technology p [€]
f_l^{stor}	Investment cost for storage type l [€]
f_q^{trans}	Distance-related investment costs for transport technology q [€ /*km*]
f_r^{RE}	Investment cost for renewable electricity sources type r [€]
c_p^{pod}	Annual operation and maintenance costs of production technology p [€ /*year*]
c_l^{stor}	Annual operation and maintenance costs of storage technology l [€ /*year*]
c_q^{trans}	Distance-related annual operation and maintenance costs of transport technology q [€ /*km.year*]
c_r^{RE}	Annual operation and maintenance cost of renewable electricity sources type r [€]
$\nu_q^{trans.dis}$	Distance-related unit transport costs of technology q [€ /*tonne.km*]
ν_q^{tran}	Unit transport costs of technology q [€ /*tonne*]
ν_{oit}	Unit purchasing costs of resource origin o in region i in period t, [€ /*tonne*]
ν_{mt}^{import}	Price of contracted import of product m in period t [€ /*tonne*]
ν_{mt}^{spot}	Price of spot import of product m in period t [€ /*tonne*]
Decision variables (Strategic)	
$\theta_{itr\chi} \geq 0$	Installed capacity of renewable electricity source r in region i up to period t for scenario χ [*MW*]
$\delta_{pit\chi} \in \mathbb{N}_0$	Number of production plants p installed in region i up to period t for scenario χ
$\gamma_{lit\chi} \in \mathbb{N}_0$	Number of storage units of storage technology l installed in region i up to period t for scenario χ
$\kappa_{qii't\chi} \in \mathbb{N}_0$	Number of transportation infrastructures $q \in Q_{inv}$ installed between region i and i' up to period t for scenario χ
$\psi_{mit\chi}^{import} \geq 0$	Amount contracted import material m to region i in period t during each season for scenario χ [*tonnes /season*]
Decision variables (Tactical)	
$\omega_{oist\chi} \geq 0$	Utilization of resource origin o in region i during period t and season s under scenario χ [*tonnes /season*], [*MWh /season*]
$x_{pist\chi} \geq 0$	Production rate of production pathways p in region i in period t during season s under scenario χ [*tonnes /season*]
$y_{lmits\chi} \geq 0$	Amount of resource stored with storage technology l in region i in period t during season s under scenario χ [*tonnes /season*]
$z_{qmii'ts\chi} \geq 0$	Amount of resource m transported from region i to i' using transport technology q in period t during season s under scenario χ [*tonnes /season*]
$\Psi_{mits\chi}^{spot} \geq 0$	Amount of spot import of material m in region i in period t during season s under scenario χ [*tonnes /season*]

3.2.1. Objective function and cost components

The objective function minimizes the expected net present value of total discounted system costs across all scenarios and time periods. A cost-minimization objective is appropriate under uncertain demand because all demand must be satisfied in every scenario, and the goal is to determine the least-cost strategy that remains feasible across all possible realizations. The formulation is given in Eq. (1).

Our framework distinguishes between two categories of decisions. Strategic decisions include investment costs for production ($\sum_{i\in I}\sum_{p\in P} f_p^{prod}\left(\delta_{pit\chi} - \delta_{pi(t-1)\chi}\right)$), storage ($f_l^{stor}\left(\gamma_{lit\chi} - \gamma_{li(t-1)\chi}\right)$), transportation ($\sum_{q\in Q_{inv}} f_q^{trans} d_{ii'}\left(\kappa_{qii't\chi} - \kappa_{qii'(t-1)\chi}\right)$), and RES facilities ($f_r^{RE}\left(\theta_{itr\chi} - \theta_{i(t-1)r\chi}\right)$), as well as operation, and maintenance (O&M) costs for these components ($c_p^{prod}\delta_{pit\chi}$, $c_l^{stor}\gamma_{lit\chi}$, $c_q^{trans} d_{ii'}\kappa_{qii't\chi}$, $c_r^{RE}\theta_{itr\chi}$), and contracted imports ($\nu_{mt}^{import}\psi_{mit\chi}^{import}$). Tactical decisions cover variable



Decision	Resources	Production	Transportation	Storage	Import
Strategic: Investments	Installed RES capacity $\theta_{itr\chi}$	Number of installed plants $\delta_{pit\chi}$	Number of installed pipelines $\kappa_{qii't\chi}$	Number of installed facilities $\gamma_{lit\chi}$	Amount of contracted import $\psi^{import}_{mits\chi}$
Tactical: Utilizations	Resource utilization $\omega_{oist\chi}$	Amount of production $x_{pist\chi}$	Amount of transportation $z_{qmii'ts\chi}$	Amount of storage $y_{lmits\chi}$	Amount of spot import $\Psi^{spot}_{mits\chi}$

Fig. 1. RFSC with sets and decision variables.

transportation quantities ($\left(\nu^{trans,dis}_{q} d_{ii'} + \nu^{tran}_{q}\right) z_{qmii'ts\chi}$), resource procurement quantities ($\omega_{oist\chi}\nu_{oit}$), and spot import quantities ($\nu^{spot}_{mt}\Psi^{spot}_{mits\chi}$). The objective function is then obtained by aggregating these cost components across all scenarios, weighted by their respective probabilities.

$$
\begin{aligned}
Min\ ETC = \sum_{t\in T}\sum_{\chi\in X}\Pr(\chi)\Bigg(
&\zeta^{sp}_{t}\Bigg(
\sum_{i\in I}\sum_{p\in P} f^{prod}_{p}\left(\delta_{pit\chi}-\delta_{pi(t-1)\chi}\right)+\sum_{i\in I}\sum_{l\in L} f^{stor}_{l}\left(\gamma_{lit\chi}-\gamma_{li(t-1)\chi}\right)\\
&+\sum_{i\in I}\sum_{i'\in I|i'\neq i}\sum_{q\in Q_{inv}} f^{trans}_{q} d_{ii'}\left(\kappa_{qii't\chi}-\kappa_{qii'(t-1)\chi}\right)+\sum_{i\in I}\sum_{r\in RE} f^{RE}_{r}\left(\theta_{itr\chi}-\theta_{i(t-1)r\chi}\right)
\Bigg)\\
&+\zeta^{yp}_{t}\Bigg(
\sum_{i\in I}\sum_{p\in P} c^{prod}_{p}\delta_{pit\chi}+\sum_{i\in I}\sum_{l\in L} c^{stor}_{l}\gamma_{lit\chi}+\sum_{i\in I}\sum_{i'\in I|i'\neq i}\sum_{q\in Q} c^{trans}_{q} d_{ii'}\kappa_{qii't\chi}+\sum_{i\in I}\sum_{r\in RE} c^{RE}_{r}\theta_{itr\chi}\\
&+\sum_{m\in M}\sum_{i\in I}\sum_{s\in S}\left(\nu^{import}_{mt}\psi^{import}_{mits\chi}\right)+\sum_{o\in O\setminus RE}\sum_{i\in I}\sum_{s\in S}\left(\omega_{oist\chi}\nu_{oit}\right)\\
&+\sum_{s\in S}\sum_{i\in I}\sum_{i'\in I|i'\neq i}\sum_{q\in Q}\sum_{m\in M}\left(\nu^{trans,dis}_{q} d_{ii'}+\nu^{tran}_{q}\right) z_{qmii'ts\chi}+\sum_{m\in M}\sum_{i\in I}\left(\nu^{spot}_{mt}\Psi^{spot}_{mits\chi}\right)
\Bigg)\Bigg)
\end{aligned}
\tag{1}
$$

Eq. (2) denotes the discounting factor for strategic decisions, and Eq. (3) shows the discounting factor for tactical decisions.

$$\zeta^{sp}_{t} = (1+\tau)^{-n(t-1)},\ t\in T \tag{2}$$

$$\zeta^{yp}_{t} = \left(\sum_{i=1}^{n}(1+\tau)^{1-i}\right)\zeta^{sp}_{t},\ t\in T \tag{3}$$

3.2.2. Constraints

In addition, the model incorporates several technical and resource-related constraints. Energy and material balances form the central condition, requiring that total supply, including fuel production across regions and time periods, net storage and transportation flows, as well as contracted and spot imports, satisfies regional demand in each period (Eq. (4)).

$$\sum_{O\in O}\beta_{om}\omega_{oits\chi} + \sum_{p\in P}\alpha_{mp}\, x_{pits\chi} + \sum_{L\in L|(l,m)\in A_{lm}}\left(y_{lmit(s-1)\chi} - y_{lmits\chi}\right) + \sum_{i'\in I}\sum_{q\in Q|(q,m)\in B_{qm}}\left(z_{qmi'its\chi} - z_{qmii'ts\chi}\right) + \psi^{import}_{mits\chi} + \Psi^{spot}_{mits\chi} \geq D_{mits\chi},\ m\in M,\ i\in I,\ t\in T,\ s\in S,\ \chi\in X \quad (4)$$

Contracted imports are limited by permitted import shares (Eq. (5)).

$$\sum_{s\in S}\sum_{i\in I}\psi^{import}_{mits\chi} \leq \upsilon_{mt},\ m\in M,\ t\in T,\ \chi\in X \quad (5)$$

The output of each production technology cannot exceed its installed capacity (Eq. (6)).

$$x_{pits\chi} \leq H' K^{prod}_{p}\delta_{pit\chi},\ p\in P,\ i\in I,\ t\in T,\ s\in S,\ \chi\in X \quad (6)$$

Storage levels are restricted by installed capacity and compatibility with designated storage types (e.g., caverns), ensuring that only suitable locations are used (Eq. (7)).

$$y_{lmits\chi} \leq K^{stor}_{l}\gamma_{lit\chi},\ t\in T,\ s\in S,\ \chi\in X,$$

$$(l,m)\in A_{lm}, (l=caverns\rightarrow i\in CI)\bigwedge(l\neq caverns\rightarrow i\in I) \quad (7)$$

Transportation flows via modes requiring infrastructure investment are bounded by installed capacity and restricted to regions where pipeline construction is feasible, thereby ensuring correct assignment of transportation modes (Eqs. (8) and (9)).

$$z_{qmii'ts\chi} \leq HK^{trans}_{q}\kappa_{qii't\chi},$$

$$q\in Q_{inv},\ m\in M,\ i,i'\in I,\ t\in T,\ s\in S,\ \chi\in X \quad (8)$$

$$z_{qmii'ts\chi} = 0,\ q\in Q,\ m\in M,\ i,i'\in I,\ t\in T,\ s\in S,$$

$$\chi\in X \mid B_{qm}=0\wedge i\neq i'\wedge B^{pipe}_{ii'}=0\ \wedge B^{truck}_{ii'}=0 \quad (9)$$

Resource use is further bounded by regional availability of feedstocks and inputs such as biomass, carbon, and water (Eq. (10)).

$$\omega_{oits\chi} \leq R_{oist},\ o\in O\setminus RE,\ i\in I,\ t\in T,\ s\in S,\ \chi\in X \quad (10)$$

The use of renewable electricity from wind and solar is limited by installed capacity, seasonal capacity factors, and the number of operating hours per season, while regional maximum installable capacities further restrict the installation of onshore and offshore facilities (Eqs. (11) and (12)).

$$\omega_{oits\chi} \leq H\theta_{itr\chi}\vartheta_{isr},\ o\in RE,\ i\in I,\ t\in T,\ s\in S,\ \chi\in X \quad (11)$$

$$\theta_{itr\chi} \leq \Theta_{ir},\ r\in RE,\ i\in I,\ t\in T,\ \chi\in X \quad (12)$$

Finally, capacity expansion is subject to monotonicity conditions: the number of production, storage, transportation, and renewable energy facilities must remain non-decreasing over time and persist throughout the planning horizon (Eqs. (13)–(16)).

$$\theta_{i(t-1)r\chi} \leq \theta_{itr\chi},\ r\in RE,\ i\in I,\ t\in T_0,\ \chi\in X \quad (13)$$

$$\delta_{pi(t-1)\chi} \leq \delta_{pit\chi},\ p\in P,\ i\in I,\ t\in T_0,\ \chi\in X \quad (14)$$

$$\gamma_{li(t-1)\chi} \leq \gamma_{lit\chi},\ l\in L,\ i\in I,\ t\in T_0,\ \chi\in X \quad (15)$$

$$\kappa_{qii'(t-1)\chi} \leq \kappa_{qii't\chi},\ q\in Q_{inv},\ i,i'\in I|i\neq i',\ t\in T_0,\ \chi\in X \quad (16)$$

Eqs. (17) and (18) denote the type of variables.

$$\kappa_{qii't\chi}, \delta_{pit\chi}, \gamma_{lit\chi}\in\mathbb{N}_0,\ q\in Q_{inv},\ p\in P,\ l\in L,\ i,i'\in I|\ i\neq i',\ t\in T_0,\ \chi\in X \quad (17)$$

$$z_{qmii'ts\chi}, x_{pist\chi}, y_{lmits\chi}, \omega_{oist\chi},\ \Psi^{spot}_{mits\chi},\ \theta_{itr\chi},\ \psi^{import}_{mits\chi} \geq 0,$$

$$q\in Q,\ p\in P,\ l\in L,\ m\in M,\ o\in O,\ i,i'\in I|i\neq i',\ t\in T,\ s\in S,\ r\in RE,\ \chi\in X \quad (18)$$

3.2.3. Non-anticipativity constraints

The Eqs. (20)–(29) show non-anticipativity constraints, which mean that only information available at a given stage is used rather than anticipating the information that will emerge after the decision has been made. A stochastic parameter realization in period t under scenario χ is presented by ξ^{χ}_{t}. The uncertainty realization from the start of the planning horizon until/to the period t under scenario χ is represented by $(\xi^{\chi}_{1}, \xi^{\chi}_{2}, \ldots, \xi^{\chi}_{t})$. The presence of the same realization in scenario sequences suggests that they share the same scenario bundle. Here the strategic decisions at each stage have to be made before the realization of stochastic parameters. The non-anticipativity constraints force the decisions made at stage t to be equal across corresponding scenario sequences. Hence, if a pair of scenarios have the same ancestor scenario (until $t-1$), both are equal at that stage (t) in the scenario tree and this approach enforces non-anticipativity.

$$\theta_{itr\chi} = \theta_{itr\chi'},\ t=1,\ r\in RE,\ i\in I,\ \chi',\chi\in X \quad (20)$$

$$\theta_{itr\chi} = \theta_{itr\chi'},\ t\in T\setminus\{1\},\ r\in RE,\ i\in I,\ \chi',\chi\in X:(\xi^{\chi}_{1},\xi^{\chi}_{2},\ldots,\xi^{\chi}_{t-1}) = (\xi^{\chi'}_{1},\xi^{\chi'}_{2},\ldots,\xi^{\chi'}_{t-1}) \quad (21)$$

$$\delta_{pit\chi} = \delta_{pit\chi'},\ t=1,\ p\in P,\ i\in I,\ \chi',\chi\in X \quad (22)$$

$$\delta_{pit\chi} = \delta_{pit\chi'},\ t\in T\setminus\{1\},\ p\in P,\ i\in I,\ \chi',\chi\in X:(\xi^{\chi}_{1},\xi^{\chi}_{2},\ldots,\xi^{\chi}_{t-1}) = (\xi^{\chi'}_{1},\xi^{\chi'}_{2},\ldots,\xi^{\chi'}_{t-1}) \quad (23)$$

$$\gamma_{lit\chi} = \gamma_{lit\chi'},\ t=1,\ l\in L,\ i\in I,\ \chi',\chi\in X \quad (24)$$

$$\gamma_{lit\chi} = \gamma_{lit\chi'},\ t\in T\setminus\{1\},\ l\in L,\ i\in I,\ \chi',\chi\in X:(\xi^{\chi}_{1},\xi^{\chi}_{2},\ldots,\xi^{\chi}_{t-1}) = (\xi^{\chi'}_{1},\xi^{\chi'}_{2},\ldots,\xi^{\chi'}_{t-1}) \quad (25)$$

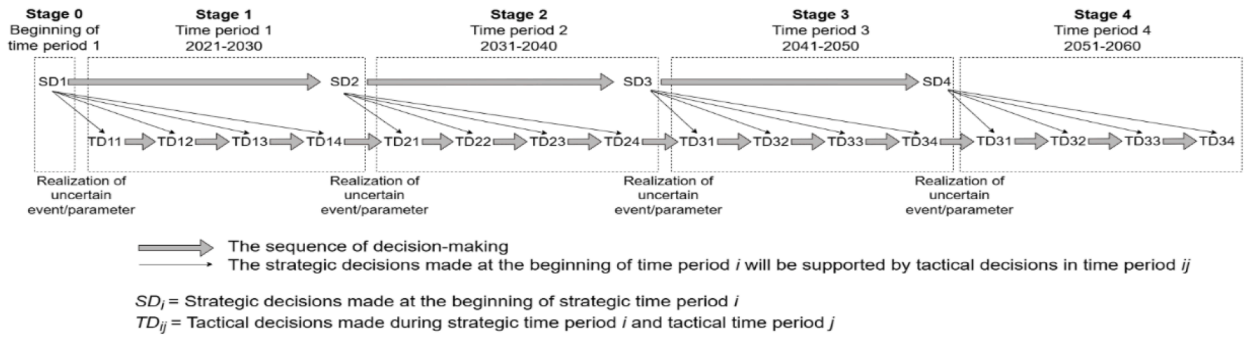


Fig. 2. Sequence of decision-making, our own illustration for our case study, adjusted based on (Xie and Huang, 2018).

$$\kappa_{qii't\chi} = \kappa_{qii't\chi'},\ t = 1,\ q \in Q_{inv},\ i,i' \in I | i \neq i',\ \chi',\chi \in \mathrm{X} \tag{26}$$

$$\kappa_{qii't\chi} = \kappa_{qii't\chi'},\ t \in T\backslash\{1\},\ q \in Q_{inv},\ i,i' \in I | i \neq i',\ \chi',\chi \in \mathrm{X} : (\xi_1^{\chi}, \xi_2^{\chi}, \ldots, \xi_{t-1}^{\chi}) = (\xi_1^{\chi'}, \xi_2^{\chi'}, \ldots, \xi_{t-1}^{\chi'}) \tag{27}$$

$$\psi_{mits\chi}^{import} = \psi_{mits\chi'}^{import},\ t = 1,\ m \in M,\ i \in I,\ \chi',\chi \in \mathrm{X},\ s \in S \tag{28}$$

$$\psi_{mits\chi}^{import} = \psi_{mits\chi'}^{import},\ t \in T\backslash\{1\},\ m \in M,\ i \in I,\ \chi',\chi \in \mathrm{X} : (\xi_1^{\chi}, \xi_2^{\chi}, \ldots, \xi_{t-1}^{\chi}) = (\xi_1^{\chi'}, \xi_2^{\chi'}, \ldots, \xi_{t-1}^{\chi'}),\ s \in S \tag{29}$$

3.3. Construction of demand scenario tree

MSSP is both computation and data-intensive due to the complexity of making sequential decisions under uncertainty. A key initial step involves discretizing (or sampling) the continuous probability distributions of uncertain parameters into an approximate distribution represented by a finite set of scenarios (Heitsch and Römisch, 2005). This approach reduces infinite-dimensional optimization problems to finite-dimensional ones by representing each scenario as a multidimensional stochastic process, which is typically more tractable than a continuous model. However, given the computational complexity of stochastic models, only a limited number of scenarios can be used, making the generation of an effective scenario tree that accurately approximates the underlying probability distribution necessary. Dupacova et al., 2003 proposed a scenario reduction methodology to avoid the problem becoming too high-dimensional, which was further developed by Heitsch and Römisch (2003, 2009).

We generate a scenario fan by using discrete scenarios to approximate the uncertainty space. To ensure a manageable number of representative scenarios, we then employ scenario reduction. This method retains the essential aspects of uncertainty while ensuring computational tractability, making it feasible to analyze complex uncertainty structures without compromising solution quality.

3.3.1. Generation of demand scenario fan

To capture demand uncertainty across multiple periods, demand in each period is treated as an uncertain parameter. Time dependencies are incorporated through an appropriate time-series representation within each scenario. Following the literature (Zimberg et al., 2019; Dilaver and Hunt, 2021), demand for different fuel types is assumed to follow a stochastic process. To account for strong temporal variability, a modified first-order autoregressive model, originally proposed by Sodhi, (2005), and later applied in several studies (Fattahi et al., 2017; Fattahi and Govindan, 2017) is employed. Based on this approach, we generate time-dependent demand scenarios per fuel. Each fuel's demand is modeled using the autoregressive process defined in Eq. (30):

$$D_{mt}^{\chi} = \mu_{mt} + \rho_m \left(D_{m,t-1}^{\chi} - \mu_{m,t-1} \right) + \epsilon_{mt}^{\chi} \tag{30}$$

Where D_{mt}^{χ} represents the demand for the fuel m at time t in scenario χ, μ_{mt} is the time-specific mean demand used to capture the development of potential demands over the planning horizon. The autoregressive coefficient ρ_m links deviations from the previous period's mean to the current demand. The stochastic error term ϵ_{mt}^{χ} assumed to follow a normal distribution with mean zero and variance σ_{ϵ}^2 introduces variability across scenarios. Different scenarios are constructed by sampling error terms via Latin Hypercube Sampling (LHS), which ensures broader coverage of the stochastic parameter space compared to a simple Monte Carlo simulation (Govindan and Fattahi, 2017; Fattahi et al., 2015). This formula captures the temporal dependence of demand, where deviations from the mean demand in the previous time period influence the current demand through the autoregressive term ρ_m. The parameters μ_{mt}, ρ_m, and σ_{ϵ}^2 are drawn from predefined ranges to reflect both product- and time-specific characteristics, thereby enabling realistic and flexible demand modeling. Model parameters are calibrated based on case study data and informed assumptions.

3.3.2. Reduction of demand scenarios

A scenario generation procedure generates a large number of instances, each representing an uncertain parameter. While increasing the number of scenarios improves the representation of uncertainty, solving stochastic optimization problems with many scenarios requires significant effort. Moreover, individual scenario probabilities become negligible, which reduces their practical relevance while still inflating computational effort. Efficient approximations that reduce the number of scenarios while preserving key characteristics are recommended (Jadidbonab et al., 2019). A survey of SPs by Römisch (Fattahi et al., 2015) and a study of TSSP models with stochastic resources by Römisch and Wets (2007) provides the basis for the methods for reducing scenarios discussed here. Based on the Monge-Kantorovich theory of mass transportation by Rachev and Rüschendorf (1998) these methods measure distances between probability distributions. As with the k-median problem, optimal scenario reduction problems are

Algorithm 1
Forward selection algorithm for reducing the number of scenarios and constructing a scenario tree.

```
Algorithm: Forward selection algorithm
Start
    Read scenario data and initialize parameters (S, T, π, ε, q)
    Initialization:
        Create an initial cluster with all scenarios: cluster "C0"
        Compute tolerance values ε_t for each time period t using q: ε_t
    For each time period t:
        Set tolerance for current cluster k in the time period t: ε_tk ← ε_t
        For each cluster k in the current time period t:
            Extract scenario data for the current node
            Reduce Scenarios within the Cluster:
                Select a representative scenario
                Compute Euclidean distances and weighted costs
                Merge scenarios if cumulative cost ≤ ε_tk
                Update mapping for merged scenarios
            Form new clusters:
                Create new cluster names based on the parent cluster and a counter
                Assign representative and merged scenarios to new clusters
            Update the cluster list for the next time period t + 1 and store results
    Final aggregation:
        Build a final mapping from the original scenarios to their representative scenarios
        For each representative, sum up the probabilities (π) of all scenarios it represents
End
```

NP-hard. The forward and backward heuristic approaches developed by Dupačová (1995) and further refined (Heitsch and Römisch, 2003; Heitsch and Römisch, 2007) have demonstrated promising results in real-world applications.

The forward selection algorithm is used in this paper. Algorithm 1 shows the steps of this algorithm. The method takes as input a finite number of user-provided scenarios, which are generated from the scenario generation procedure in the previous step. Iterative scenario selection is then performed using a recursive (optimal) scenario reduction process. Starting with an empty set, an iterative process is carried out until the termination criteria are met. During each iteration, the scenario with the lowest Kantorovich distance between the reduced and original sets is selected and inserted into the reduced set. In the algorithm, $t \in T$ denotes the number of time periods and S the original number of scenarios. The parameter q governs the decay of individual tolerances over time, thereby shaping the branching structure. ε represents the general tolerance for scenario reduction, while ε_t specifies the individual tolerance applied at the time period t, and ε_{tk} indicates the tolerance for the current cluster at time t. Scenario probabilities are denoted by π.

The methodology can be summarized as follows: It is assumed that each scenario generated at each node is equally likely. Rather than targeting a predetermined number of scenarios, the algorithm employs a recursive, optimal scenario reduction process driven by threshold values. At each time period, a tolerance threshold is used to assess the similarity between scenarios. Specifically, the Euclidean distance between every pair of scenarios at a given node is computed and weighted by their respective probabilities to construct an aggregated cost function. In each iteration, a representative scenario is selected from a cluster, and additional scenarios are merged into this representative only if the cumulative weighted cost remains below the tolerance threshold. The cost matrix is then updated by substituting each element with the minimum between the original cost and that associated with the chosen representative. This merging process is iteratively applied over successive time periods until no further merging is possible without exceeding the specified threshold. Finally, the probabilities of the non-selected scenarios are redistributed to the representative ones, so that each retained scenario's probability becomes the sum of its original probability and those of its merged counterparts, while the probabilities of eliminated scenarios are set to zero.

4. Case study

We implement our method in a real-world country-specific EU case study. The target is to meet the future fuel demand of the transportation sector within the time frame of 2021 to 2060. We break the time horizon into ten-year strategic periods. Consequently, there are four strategic periods, with investment decisions made at the start of each decade (T1: 2021–2030, T2: 2031–2040, T3: 2041–2050, T4: 2051–2060). We represent seasonal resource availability using four seasons: spring (Mar–May), summer (Jun–Aug), autumn (Sep–Nov), and winter (Dec–Feb). Each production and transport facility is available for a maximum of 1,752 hours per season (80% utilization), accounting for planned and unplanned shutdowns, with no reserve capacity assumed (Larson et al., 2009).

Biomass supply by region and decade follows the ENSPRESO reference scenario (European Commission Joint Research center, 2019), with seasonal availability determined by allocating individual products to their harvest periods (Čuček et al., 2014). For solar and wind onshore/offshore, maximum installable capacities are taken from the reference scenario of ENSPRESO (European Commission Joint Research center 2019b, 2019c), and their capacity factors are based on the renewable ninjas database (Renewables.ninja 2016; Pfenninger and Staffell, 2016; Staffell and Pfenninger, 2016). Hydrogen production is assumed to rely on freshwater, with national freshwater potentials obtained from Eurostat (E. 2022 European Commission, 2022). Biomass prices follow the ENSPRESO reference scenario (European Commission Joint Research center, 2019). Water prices are taken from the governance of European water services (Varone and Ferrari, 2015; EurEau, 2020). CO_2 prices from industrial and biogenic sources are based on Brynolf et al. (2018). We assume that max 50% of the biomass potential and renewable electricity potential is available for the transportation sector, to regard for competition for resources, based on a study by FVV study FVV (2021).

We assume no production facilities exist at the start of the planning horizon. The technologies considered are BtL, PBtL, and PtL for FT-fuels and MeOH, PEM and AEL electrolyzers for H_2, and Haber–Bosch for NH_3, with techno-economic data FVV (2021) and Vos et al. (2020). Three capacity levels with associated costs are modeled for most technologies FVV (2021). To reflect technological progress and scale up, the model ensures these pathways are not static; rather, the smallest capacity is available in period 1, with larger, more efficient capacities becoming available in periods 2 and 4 to reflect technological progress in cost, efficiency, and scale. For Haber–Bosch, only two capacities are included from period 1 onwards (Fasihi et al., 2021). DAC and ASU are represented by a single capacity available throughout. CAPEX and OPEX for RES are adopted (EurEau, 2020).

We model two pipeline capacities for CO_2 (Fasihi et al., 2019; McCollum and Ogden, 2006) and three capacities for H_2 pipelines based on the European Hydrogen Backbone (EHB) initiative (Wang et al., 2020). Only new H_2 pipelines are considered, since much of today's natural gas infrastructure is unsuitable for long-distance transport, incurs higher O&M costs, and its long-term availability remains uncertain. Distances between country centroids are calculated via the haversine function. Storage options include CO_2 from DAC, H_2, FT-fuels, MeOH, and NH_3, with H_2 caverns available only in selected countries (Bulgaria, Germany, Denmark, France, Netherlands, Poland, Portugal, UK).

Future demand for renewable fuels in Europe is expected to increase substantially. H_2 demand is estimated based on the EHB projections for aviation and heavy-duty transport, supplemented by the demand for bio- and synthetic kerosene (Wang et al., 2021). For FT-fuels, MeOH, and NH_3, global projection data from (Galimova et al., 2023) are used, with European demand adjusted by excluding countries outside the scope of this case study, namely Norway, the Western Balkans, Switzerland, Liechtenstein, Turkey, Cyprus, Ukraine, Moldova, and Iceland. According to this study, nearly all FT-fuel consumption is expected to occur within the transport sector. For NH_3, we assume a smooth transition over time in the first decade, targeting an overall 5% share of total demand originating from transport applications, as most ammonia is still used for fertilizer and chemical production. The projected shares for the following decades are based on literature, increasing to 10% by 2030, reflecting the gradual uptake in maritime transport, and reaching approximately 25% by 2050 in line with Net-Zero Emissions shipping demand forecasts (I. Energy Agency, 2024a, 2024b). For MeOH, we similarly assume a smooth transition within the first decade, with transport accounting for about 38% of total demand, including its use as a fuel additive and direct fuel in road and marine transport. The projections for subsequent decades are taken from literature, suggesting that this share remains around 38% by 2030 and increases to roughly 77% by 2050, driven primarily by its role in marine fuels and as a precursor for sustainable aviation fuels (SAF) (I. Energy Agency, 2024; A.M. Analytics, 2024). Finally, country-level demand values are distributed proportionally to national populations.

It is possible to satisfy fuel demand from contracted imports from other, not further specified countries outside the EU and the UK. We assume that no >30% of the fuel demand can be met by contracted fuel imports to achieve independence in energy provision and to account for the limited availability of imported fuels (EurEau, 2020). We account for demand uncertainty; if the fuel demand can't be satisfied by the share of internal production and contracted imports, then spot imports are allowed with a penalty cost higher than the contracted import cost. For this study, since there is no fixed spot-to-contract ratio in the market, we adopt the same ratio of spot to contracted import prices as observed in

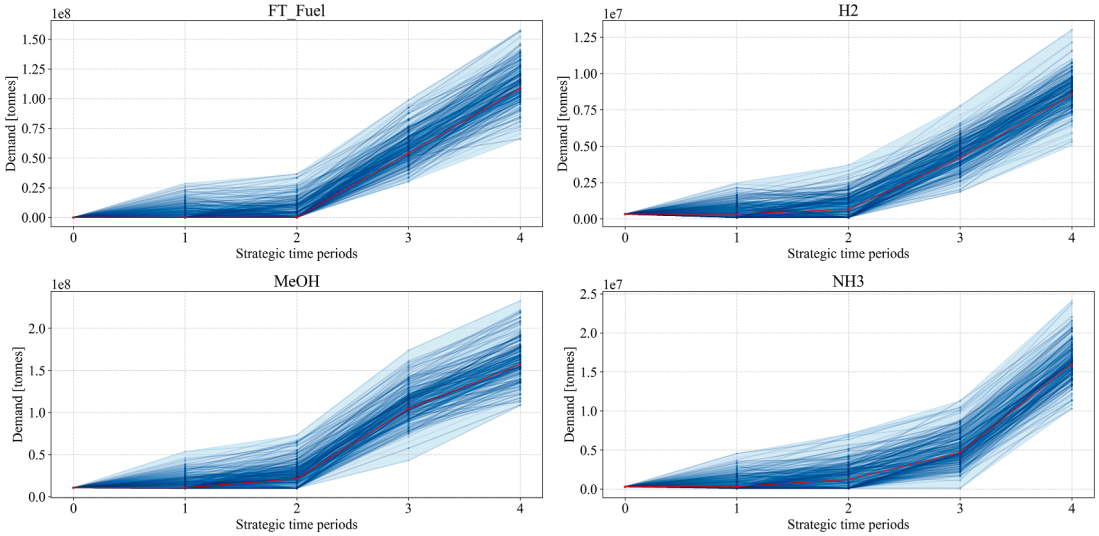


Fig. 3. Demand scenario fan generated for the future demand of each fuel type.

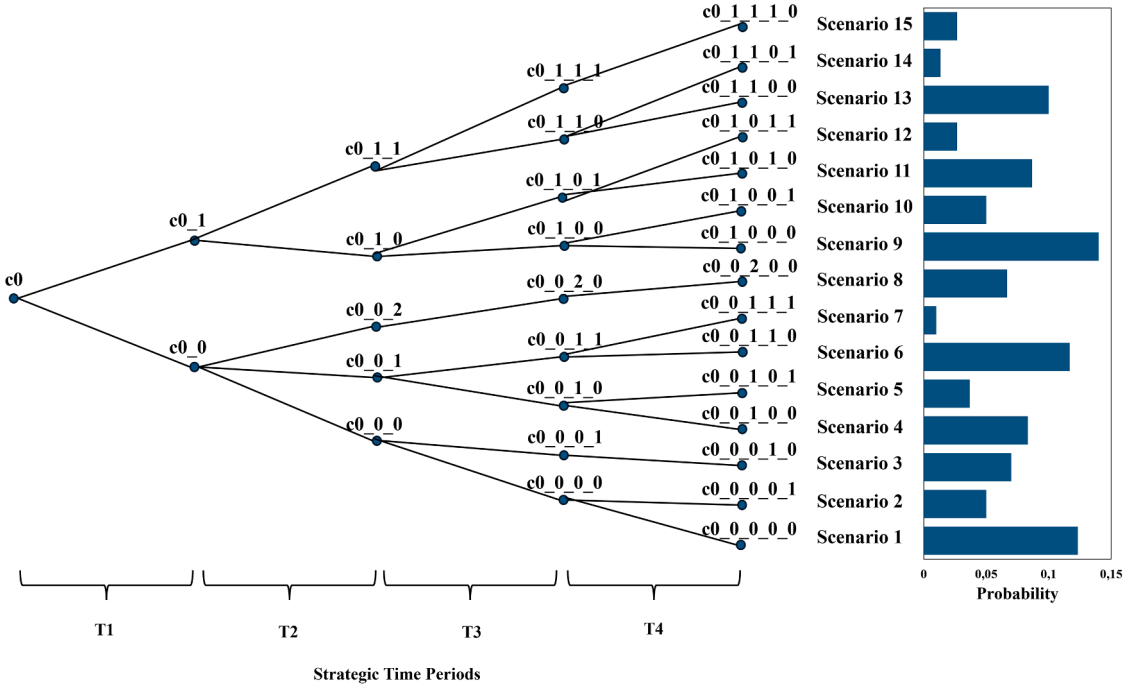


Fig. 4. Scenario tree generated using the forward selection algorithm.

the LNG market. This choice is based on historical evidence and the fact that long-term gas contracts remain the predominant pricing mechanism across most of continental Europe, reflecting the structural and pricing similarities between the two markets (Asche et al., 2013). We assume that the price per ton of spot imports is 3 times higher than that of contracted imports. All data parameters used in this case study, including their references, is available in the Supplementary Material.

4.1. Demand scenario tree for European markets

As mentioned, we focus on demand uncertainty and generate 300 distinct demand scenarios per fuel type. Each fuel's demand is modeled

Table 2
Computational characteristics and solution performance of the optimization models.

Model	Constraints	Variables	Integer variables	Nonzeros	Runtime [s]	Final gap [%]
MSSP_Base	10,399,735	19,114,831	327,600	382,937,689	50,009.9	6.12
EV	601,677	1,274,323	21,840	25,378,817	1,551.3	2.00
EEV	10,461,511	19,114,831	327,600	382,892,371	2,669.6	0.00
WS (Average, scen1–15)	601,677	1,274,323	21,840	25,378,817	1,582.0	1.96
WS (Range, scen1–15)	601,677	1,274,323	21,840	25,378,817	966.8 – 4,681.4	1.65 – 2.00

using an autoregressive process. By applying the forward selection algorithm, we identify 15 final scenarios to use in our model.

Fig. 3 illustrates the demand scenario fan for each fuel, with the red line representing the deterministic demand trajectory from reference data. In the case study, uncertainty increases over time as average demand rises. Negative scenario values, appearing only in early periods (T1, T2) due to low mean and symmetric variation, are excluded. Eq. (30) ensures that each scenario reverts toward its fuel-specific mean path while allowing random shocks ϵ^{χ}_{mt}. As a first-order autoregressive process, abrupt changes in mean demand μ_{mt} are transmitted almost directly to the simulated series, producing visible jumps. The size of these jumps depends on $\Delta\mu_{mt} = \mu_{mt} - \mu_{m,t-1}$ and the autoregressive coefficient ρ_m, with lower ρ_m amplifies discontinuities. Random shocks widen dispersion but do not smooth these shifts. Although this behavior is consistent with Eq. (30), it may exaggerate short-term volatility if actual demand evolves more gradually. Thus, the pronounced increase in variation from T0 to T4, particularly in T3, T4, stems from the fuel-specific forecasted demand trajectories used in the case study, which project strong growth in the final two decades. As a result, the generated scenarios exhibit higher absolute demand levels and broader spreads in later periods. Fig. 4 shows the scenario tree generated based on the scenario fan using the forward selection reduction algorithm. The data, parameters, and values defining the scenario fan, along with the algorithm parameters and the resulting reduced scenarios, are all provided in the Supplementary Material.

5. Results and discussion

We evaluate the developed stochastic model and scenario generation procedure in this section.

The developed MSSP model is implemented and solved using Gurobi Optimizer 12.0.2 on a virtual machine equipped with an AMD EPYC 9334 32-Core Processor (16 cores, 16 threads) and 250 GB RAM. The original model consists of 10,399,735 constraints, 19,114,831 variables, and 382,937,689 nonzero coefficients. Among the variables, 327,600 are integer variables (0 binary), while the remaining variables are continuous. After presolve reductions by Gurobi, the model size was reduced to 635,715 constraints and 705,571 variables. We impose a time limit of 50,000 seconds and a relative optimality gap tolerance of 2%. Due to the computational complexity of the large-scale MSSP formulation, the solver terminated at the imposed time limit with a final optimality gap of 6.12%. For all other computations, the same machine with same time and gap limitations is used. Table 2 summarizes the computational characteristics of the different optimization models. The full MSSP formulation is substantially larger and computationally more demanding than the deterministic EV and individual scenario models in WS solution due to the explicit representation of sequential uncertainty and non-anticipativity constraints across multiple stages.

The optimal solution defines the overall SC costs and configuration, encompassing the location, type, and capacity of production, storage, transportation, and renewable electricity technologies, as well as resource allocation decisions. It also specifies the quantities of contracted and spot imports, and the volumes of resources produced, stored, transported, and utilized over the entire planning horizon. Here, we present and discuss the key results.

The expected value of total costs across all scenarios is 2.49 [Trillion €], reflecting the aggregated investment, operation, transportation, and all procurement costs over the planning horizon. Fig. 5 visualizes the expected total cost distribution across six major cost items. Production dominates the cost structure, accounting for the largest share at 41.6% including both production investment and O&M costs. This is followed by RES with a substantial 34.8% again, including both investment and O&M costs of RES. Results indicate that these two categories together make up over three-quarters of the overall costs. This finding underscores that the economic viability of the renewable fuel transition hinges primarily on capital allocation to production facilities and renewable electricity technologies. Resources, including biomass, water, and carbon sources, contribute 10.0%, while spot import and contracted import represent 7.6% and 5.8%, respectively. In contrast, storage & transport play a minimal role in the total cost, comprising just 0.2%.

Each cost item is further broken down by time period (T1–T4), offering insights into temporal spending patterns. Notably, T3 emerges as the period with the highest overall cost, accounting for 46.0% of the total costs, significantly higher than T4, which represents 36.5%. T1 and T2 contribute 8.6% and 8.8%, respectively. This sharp rise in T3 and T4 is largely attributed to demand development and a notable increase

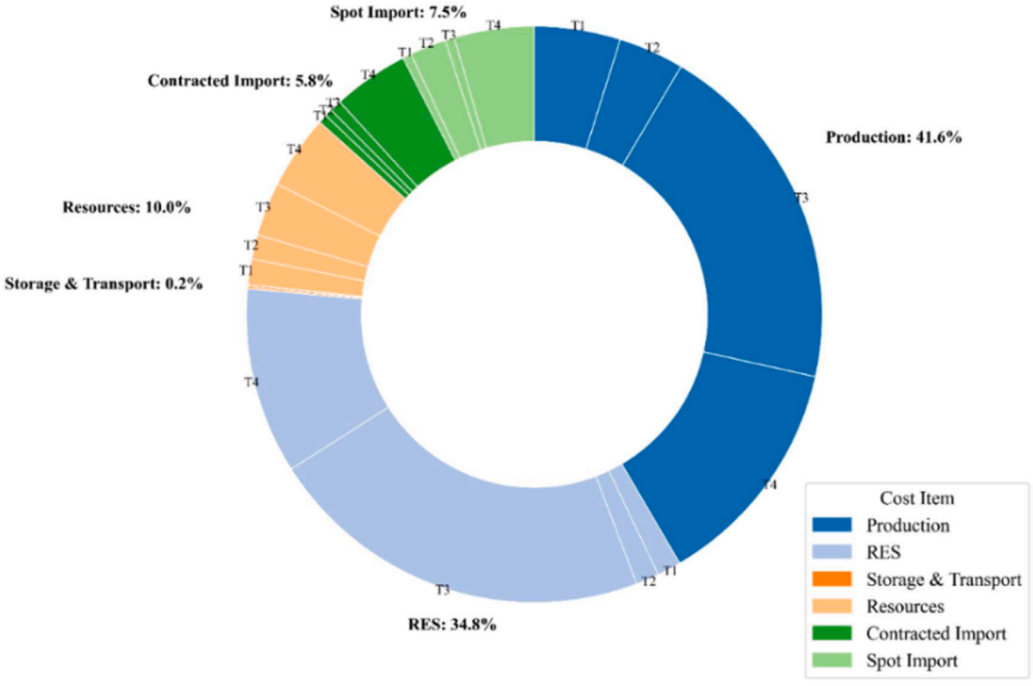


Fig. 5. Expected cost structure.

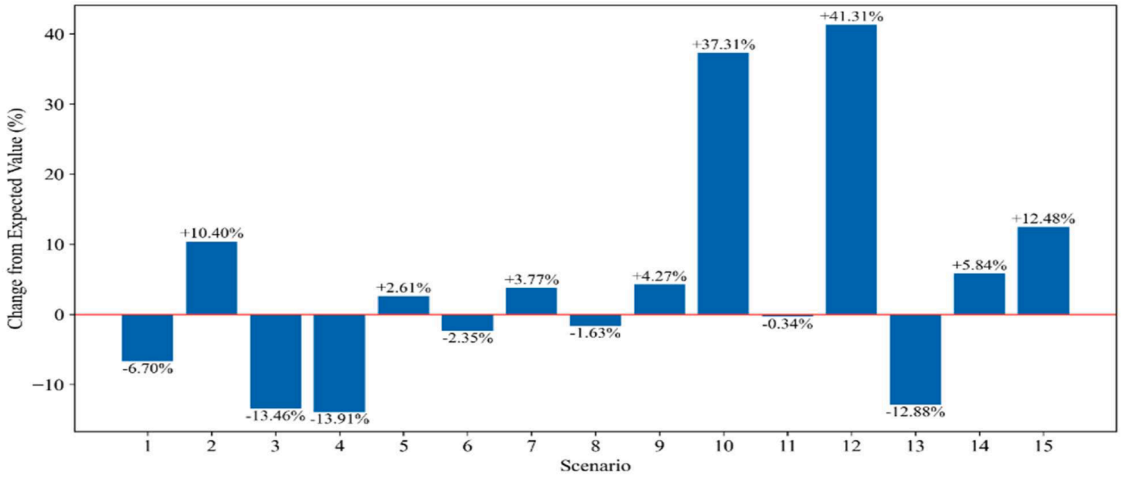


Fig. 6. Percentage changes of the total cost of each scenario relative to the expected total costs.

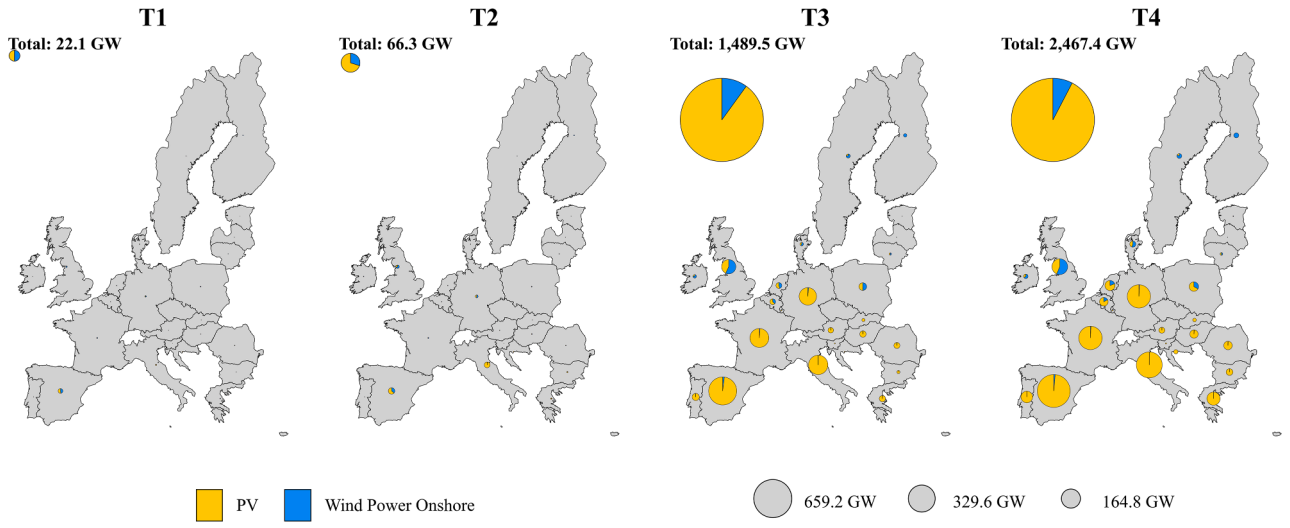


Fig. 7. Expected RES installation in different countries over strategic time periods.

during these periods. This result pronounced escalation corresponds to the strong demand development in later stages (T3, T4) and the associated capacity expansions.

In Fig. 6 shows percentage changes relative to the expected value of total costs across all scenarios. Among the scenarios, scenario 12 and scenario 10 stand out as having the highest costs, exceeding the expected value by 41.31% and 37.31% respectively, suggesting significantly more costly outcomes associated with higher demand cases. These high-demand conditions intensify import dependence and infrastructure expansion. On the other hand, Scen4 and Scen3 show the lowest cost, being 13.91% and 13.46% below the expected value over all scenarios, respectively, corresponding to the lowest demand cases. Only Scen11 is nearly identical to the expected value, with a negligible -0.34% difference.

Scenario analysis reveals substantial heterogeneity in costs, with total expenditures ranging from −13.9% to +41.3% relative to the expected value. The observed dispersion indicates that the scenario set adequately captures diverse and plausible demand conditions, providing a robust basis for assessing system performance under varying circumstances and highlighting the strong influence of demand uncertainty on total system expenditures and investment pathways.

Fig. 7 shows the expected capacity of RES installation over all scenarios and in all countries. To meet the projected fuel demand, the results indicate a substantial expansion of solar and wind power installations over the four strategic periods (T1–T4). Solar capacity exhibits an extraordinary rise from 11.1 GW in T1 to 2,315.3 GW in T4. This growth is driven by countries such as Spain (from 7.3 GW to 650.0 GW), Italy (from 0.85 GW to 408.1 GW), Germany (from 0.7 GW to 328.6 GW), and France (from 0.3 GW to 332.8 GW). Wind capacity also grows significantly but at a steadier pace, growing from 11.1 GW in T1 to 188.7 GW in T4. The United Kingdom leads in wind capacity, increasing from 1.1 GW to 85.3 GW, followed by Sweden and Finland. Several countries show uneven development between solar and wind; for instance, Croatia and Slovakia expanded solar but have no wind installations, while Finland invests heavily in wind without developing solar.

In this framework, the extensive expansion of renewable capacities arises endogenously as a consequence of the assumed demand for wind- and solar-based fuels; the model cannot satisfy this demand without a manifold increase in RES installations. The model determines the technology mix, the spatial allocation across countries, and the temporal rollout across decision stages (T1–T4). Under uncertainty, the multi-stage formulation enables early, diversified investments that hedge against future variability, with later stages adapting as more information becomes available. By T4, most countries approach their estimated potential for renewable deployment. The resulting regional heterogeneity

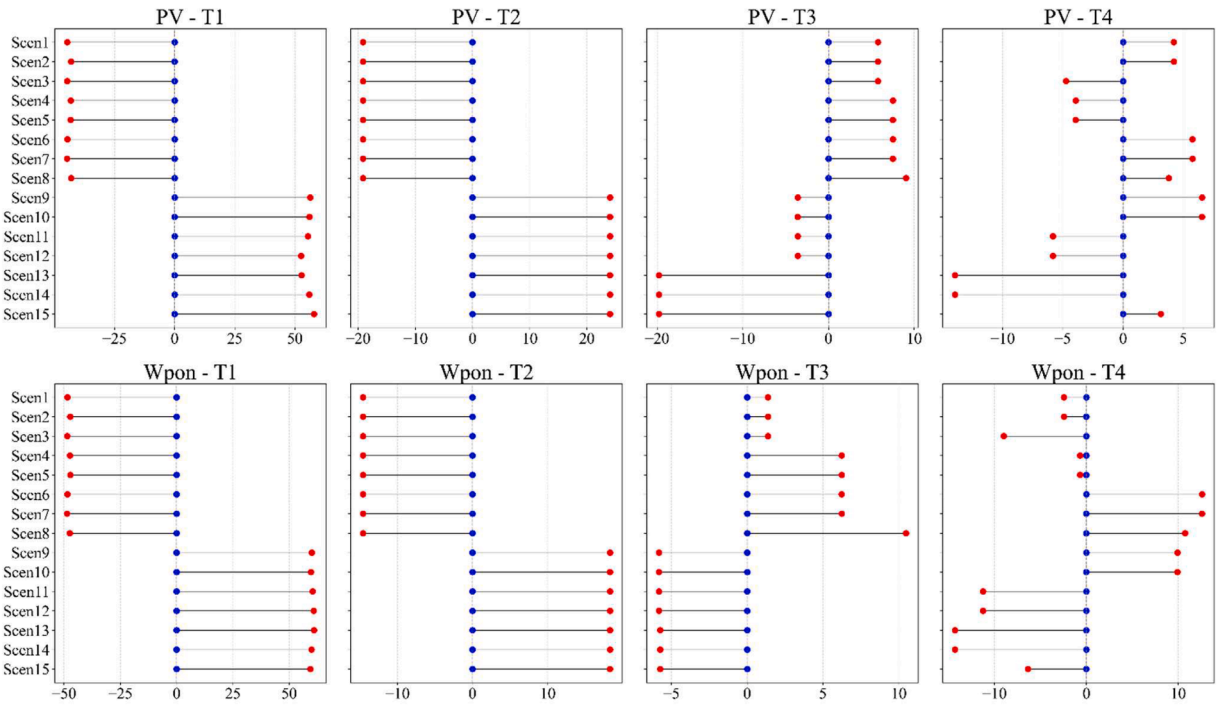


Fig. 8. percentage of deviation from expected RES installed in each scenario and time period.

thus represents an endogenous outcome of cost, resource, and uncertainty interactions. Country patterns are heterogeneous. Some countries emphasize one technology, suggesting that policy instruments should remain country-differentiated rather than one-size-fits-all. Solar dominates the renewable mix, reflecting cost competitiveness, scalability, and broad geographical potential.

Fig. 8 shows the percentage changes from the expected values of RES installations across different scenarios and time periods, using dumbbell plots to show divergence from the baseline (0%). For solar power, deviations are most pronounced in T1, where scenarios divide into two distinct groups. Scenarios 1–8 show significantly lower installation (−45 to −43%), while Scenarios 9–15 display significantly higher installation, exceeding +50% in most cases (e.g., Scen15 ≈ +58%). This early divergence reflects structural differences in the underlying demand branches. In T2, the two groups persist but converge slightly: scenarios 1–8 remain around −19%, whereas scenarios 9–15 stabilize near +24%,

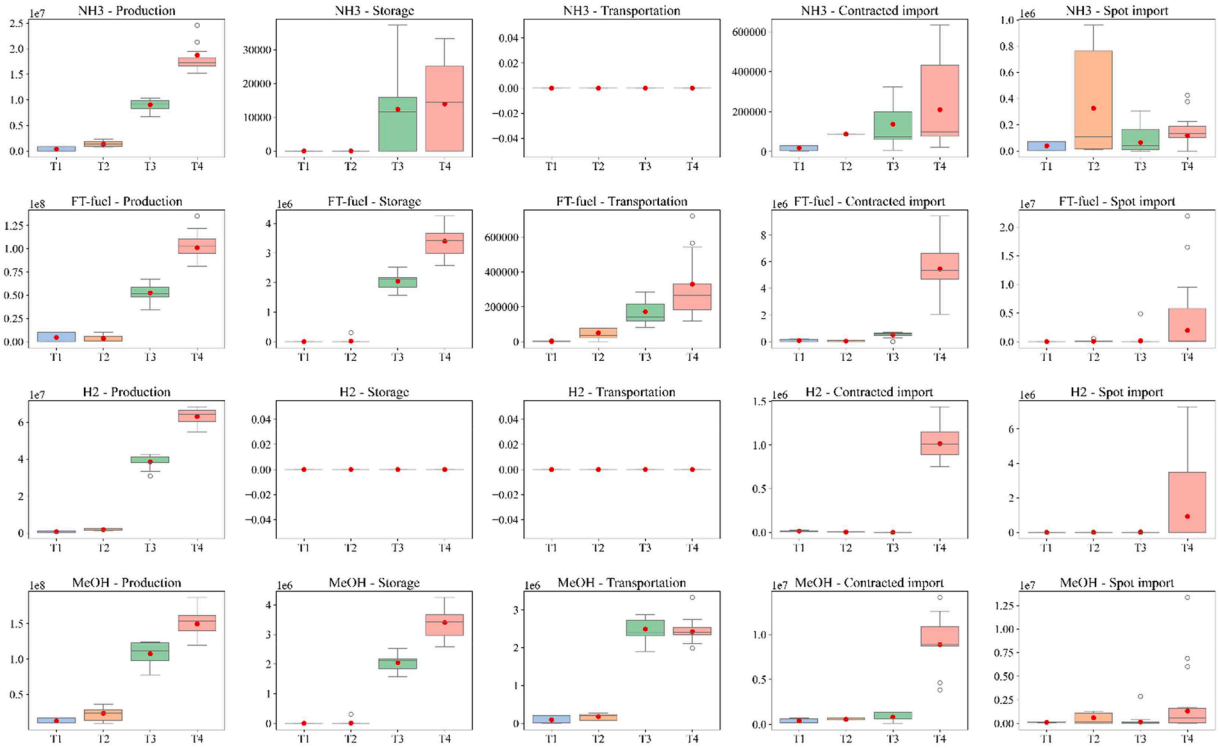


Fig. 9. Demand fulfillment of different fuels across strategic time periods and for different scenarios.

indicating continued but less volatile higher installation. By T3, the trend reverses, scenarios 1–8 approach expected values (+6–9%), while scenarios 9–15 drop below expected values (down to −20%). In T4, deviations narrow further (−5.8 to +6.6%), suggesting convergence across all scenarios as RES installations approach capacity limitation.

To analyze how renewable installations evolve across scenarios and over time, the results show distinct divergence and gradual convergence patterns for onshore wind power. In T1, the model exhibits an early bifurcation: scenarios 1–8 invest less (−49% to −47%), while scenarios 9–15 exceed the expected value by +59% to +61%. This divergence reflects differing early-stage investment decisions in response to uncertain demand realizations and technology cost assumptions. In T2, deviations narrow (−14.6% to +18.3%), as subsequent decision stages partially compensate for earlier differences once more information about demand becomes available. In T3, variability rises again as new scenario branches emerge, leading to differentiated adjustments. Higher-installation scenarios in the last period stabilize near −6%, while lower-installation ones approach the expected value (+1.4% to +10.5%). By T4, deviations lie within −14.3% to +12.6%, showing slightly greater fluctuation than for PV but an overall trend toward convergence.

Overall, both technologies display an early structural split that evolves over time as the demand scenario tree branches out, introducing new variations in later periods. These branching effects drive deviations in intermediate stages, yet the overall spread narrows as the system stabilizes near its feasible renewable capacity levels and installation trajectories converge toward their expected values. This convergence is not imposed exogenously but emerges endogenously as the model approaches renewable capacity potentials in several countries, where resource limits constrain further expansion. Overall, the pattern illustrates how early-stage uncertainty propagates through the multistage decision tree, initially amplifying variability and later narrowing as the system stabilizes near its feasible renewable capacity levels. Deviations narrow over time as investments mature and the system approaches saturation. The pattern implies two planning takeaways: (i) early decisions should be robust to the demand branch (to avoid path-dependent higher/lower investment), and (ii) flexibility built early reduces regret later as scenarios converge.

Fig. 9 shows box plots of production, storage, transportation, spot import, and contracted import across four time periods for each fuel, illustrating the demand fulfillment strategy employed under different scenarios, with red dots showing the expected value over all scenarios

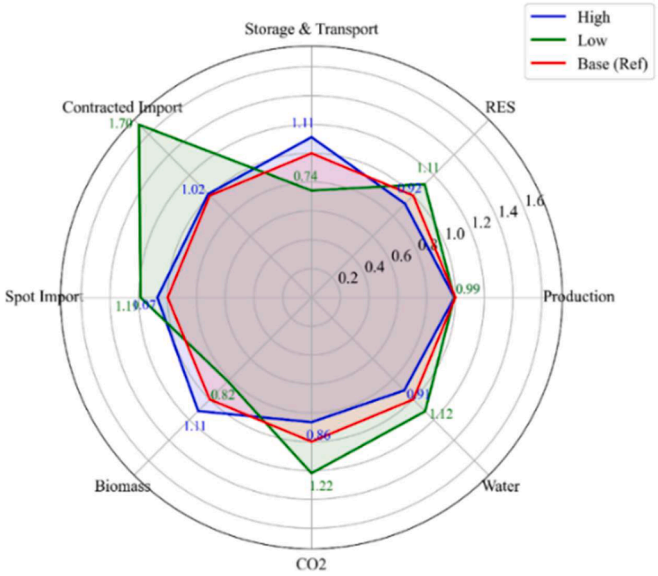


Fig. 10. changes in the cost items across different availability cases.

for each item. NH_3's supply strategy evolves toward stronger domestic production dominance in later periods (T3–T4). Contracted imports provide a stable backbone across all periods, while spot imports offer flexibility under high-demand conditions. The minimal use of storage and transport suggests a near just-in-time structure, where adaptability is primarily achieved through trade channels rather than logistics infrastructure. H_2 relies heavily on contracted imports throughout the horizon, with this dependence intensifying in T4. Domestic production remains steady, while storage and transport activities are negligible. This indicates a tightly coupled production–consumption system with limited buffering capacity. In a few high-demand scenarios, spot imports compensate for shortfalls in production or contracted imports, highlighting H_2's sensitivity to supply disruptions. FT-fuel demonstrates the diversified strategy. Domestic production increases significantly from T2 onward, complemented by substantial use of transport and storage infrastructure. Contracted imports play an important role in later stages, and spot imports are activated under extreme demand. This mix of production, logistics, and procurement pathways reflects a robust multichannel system capable of absorbing shocks and adjusting to varying conditions. MeOH maintains consistently high domestic production across all periods, with a notable surge in T4. It exhibits the broadest utilization of storage and transport, alongside a versatile combination of contracted and spot imports under high-demand scenarios. These characteristics signal MeOH's scalability.

FT-fuel and MeOH dominate total production and imports, highlighting their central role in RFSC. Both rely on diversified, logistics-intensive strategies with substantial domestic output, significant storage and transport, and a balanced mix of contracted and spot imports, yielding stable yet flexible supply structures. In contrast, H_2 and NH_3 follow import-dependent, low-logistics pathways with limited storage and transport, relying more heavily on external flexibility through trade. While domestic production underpins all fuels, their levels of diversification and flexibility differ due to both model-driven factors (e.g., storage options, conversion roles, cost assumptions) and fuel-specific techno-economic traits (e.g., transportability, storage capability, competitiveness). These differences emerge endogenously from the model's multistage adaptation to demand uncertainty. Scenario variations mainly affect the volume and timing of spot imports, while each fuel's fundamental supply pattern remains stable.

5.1. *Sensitivity analysis of resource availability*

As outlined in the case study section, the baseline assumes that 50% of the total biomass and RES potential is available for the transport sector. To assess the sensitivity of this assumption, two alternative cases are examined: a high-availability case, where 70% of the potential is accessible, and a low-availability case, where only 30% is available for the transport sector. The impact of these variations on the expected total cost is then evaluated.

Fig. 10 compares the normalized cost structure across the high-, low-, and base-availability cases. In the high-availability case, overall system costs decline slightly, with notable reductions in RES (−8.1 %) and CO_2 (−13.5 %). Notable cost increases occur in storage & transport (+11.2 %) and biomass (+11.4 %), suggesting intensified utilization and handling of local feedstocks. Conversely, in the low-availability case, the system becomes strongly import-dependent: Contracted import rises dramatically by +69.5 %, and spot import by +18.8 %, as limited RES and biomass availability force higher external sourcing. CO_2 (+21.9 %) and RES (+11.2 %) costs also increase. Declines occur in storage & transport (−25.8 %) and biomass (−17.8 %), driven by lower domestic activity. Overall, the low-availability scenario exerts a far greater impact on total costs than the high-availability case, underscoring that resource scarcity amplifies import dependence, whereas abundant renewable potential stabilizes and reduces system costs through enhanced self-sufficiency.

The sensitivity analysis highlights that resource availability is a

Table 3
Performance evaluation.

Approaches	*EV*	*EEV*	*WS*	*MSSP*	*EVPI*	*RVMSS*
Values [trillion €]	2.09	2.97	2.18	2.49	14.2%	19.4%

critical determinant of system cost and import dependence. The interplay between biomass and RES availability strongly influences system costs and energy sourcing strategies. In the high-availability case, abundant biomass enables substitution away from electricity-intensive production routes, thereby reducing RES and CO_2 costs while slightly increasing biomass and transport expenditures due to intensified domestic utilization and handling of renewable feedstocks. Conversely, when biomass and RES potentials are limited, the system compensates through higher import reliance, leading to sharp increases in contracted and spot import costs, while domestic biomass and transport expenditures decline. Overall, resource abundance enhances cost efficiency and resilience through flexible substitution between biomass and RES pathways, whereas scarcity amplifies external dependence and overall costs. This asymmetry indicates that total costs are far more sensitive to scarcity than to abundance and underscores the importance of policies that safeguard domestic resource availability (biomass mobilization, RES siting, and grid enablement) as a hedge against costly import exposure.

5.2. Evaluating the impact of MSSP

To evaluate how uncertainty influences planning decisions, this study employs the Expected Value of Perfect Information (EVPI), a metric quantifying the magnitude of potential losses due to uncertainty (Birge and Louveaux, 2011). EVPI represents the highest amount a decision-maker would theoretically pay to obtain perfect knowledge of future scenarios (Birge, 1982). Mathematically, it is calculated as the difference between the "Wait and See" (WS) solution, where decisions are postponed until uncertainties are fully revealed, and the "Here and Now" (MSSP) solution.

$$EVPI = MSSP - WS \text{ (for minimization problems)} \tag{31}$$

A second measure, the Relative Value of the Multi-Stage Stochastic Solution (RVMSS), was employed to evaluate the benefits of using MSSP compared to deterministic models (Nickel et al., 2012). The RVMSS quantifies potential cost reductions achievable by incorporating stochastic decisions. Specifically, RVMSS represents the cost difference between the MSSP solution and the EEV. The EEV is obtained by solving a deterministic model using expected parameter values (EV), then evaluating its performance under all scenarios.

$$RVMSS = EEV - MSSP/MSSP * 100 \text{ (for minimization problems)}, \tag{32}$$

In the presented case study, the EVPI was determined to be 14.2% of the WS solution. This value emphasizes the relevant impact uncertainty has on planning decisions within the examined SC. Specifically, it implies that operating without complete information carries considerable economic risk. Consequently, even modest improvements in predictive accuracy could substantially enhance decision-making outcomes and lead to significant financial savings. Furthermore, the RVMSS reached 19.4%. Such high values clearly demonstrate the substantial economic advantages offered by the MSSP model. This RVMSS indicates that MSSP notably outperforms deterministic solutions. These results confirm the importance and effectiveness of employing MSSP methods in scenarios characterized by high complexity and uncertainty. Table 3 shows the value of performance metrics. These findings validate the effectiveness of the MSSP approach in high-dimensional, uncertain energy system planning, where deterministic simplifications would otherwise lead to substantial economic inefficiencies.

6. Conclusion and outlook

This paper develops a multistage stochastic MILP framework to support long-term renewable-fuel logistics and SC network design under demand uncertainty. By integrating both strategic and tactical decisions over multiple periods, the proposed approach effectively captures how decisions must adapt as new information about uncertain parameters unfolds. A data-driven scenario construction procedure, autoregressive demand modeling combined with a forward-selection scenario reduction algorithm, enables a tractable yet representative scenario tree for large-scale, multi-decade planning. Using this model in an EU case study demonstrates its practicality and adaptability, offering valuable insights into how uncertainty can be systematically integrated into the SC of renewable fuels for the transportation sector, a crucial step toward achieving sustainability.

The results show that explicitly accounting for demand uncertainty in a sequential decision-making process enables more cost-efficient and resilient infrastructure development. By jointly optimizing investment timing, technology mix, and resource flows, the model identifies adaptive strategies that balance cost efficiency with flexibility. Technology costs, regional resource potentials, and demand variability jointly shape a diverse and robust SC portfolio over time. The results underscore that production and renewable electricity technologies dominate total system costs, confirming their pivotal role in the transition toward renewable fuels. High-demand scenarios lead to sharp cost increases and import dependence, whereas abundant domestic resource availability, particularly biomass, significantly lowers costs through enhanced self-sufficiency. Fuel-pathway differences matter for logistics design. MeOH and FT-fuels follow diversified fulfillment strategies, while H_2 and NH_3 rely more heavily on imports, highlighting differentiated infrastructure and policy needs across pathways. Performance metrics confirm the advantage of stochastic planning: the RVMSS (19.4%) indicates substantial cost savings relative to deterministic approaches, and the EVPI (14.2%) quantifies the penalty of uncertainty. Together, these findings demonstrate that MSSP provides a robust and computationally viable framework for addressing uncertainty in complex, long-term energy system planning.

Beyond its analytical contributions, this framework provides decision-makers with a structured tool to improve the efficiency, robustness, and sustainability of their long-term planning. As the world strives to become more reliant on renewable energy in the future, the insights and methodologies presented here will be important for shaping strategies and solutions.

Despite offering comprehensive insights into optimal capacity expansion and SC operations under uncertainty, several limitations should be acknowledged. First, our study centers on demand uncertainty. Other parameters are also subject to uncertainties, but are not explicitly modeled. Including multiple interacting uncertainties may further affect infrastructure and sourcing decisions. Second, in our case study, we use decadal strategic periods and four seasons per year for tactical decisions. While this captures major shifts and seasonal variations, it may overlook finer-grained operational intricacies (e.g., daily or monthly demand fluctuations and intraday electricity price spikes). The adopted representative-year approach for each strategic decade improves computational tractability and enables the solution of the large-scale multistage stochastic problem. However, this aggregation suppresses interannual variability and may therefore overlook year-to-year fluctuations in renewable resource availability, operational conditions, and demand evolution. Third, incorporating higher-frequency data could enhance realistic modeling but would further increase computational demands. Fourth, the logistics structure is simplified by modeling storage and transportation as aggregate flows, and pipeline capacities are assumed to remain fixed over the planning horizon, abstracting from regulatory, retrofitting, and public acceptance constraints. Moreover, the assumption that current pathways remain functional through 2060 may overlook potential paradigm-shifting technologies emerging later

in the horizon.

This study opens several avenues for further development of the MSSP framework. Methodologically, extending the model to include additional uncertain parameters, such as feedstock availability, technology performance, and policy incentives, would provide a more holistic representation of real-world variability. Incorporating explicit techno-economic learning curves and innovation dynamics, particularly in electrolysis, carbon capture, and synthesis processes, would refine long-term cost projections and capture the potential impact of technological breakthroughs before 2050. From a modeling standpoint, integrating market mechanisms and policy instruments (e.g., carbon pricing, feed-in tariffs, and subsidy schemes) could better reflect system-level interactions and policy feedbacks. Multi-objective extensions would enable systematic evaluation of trade-offs between cost efficiency and environmental sustainability, including emissions, biomass utilization, and transport intensity. Computationally, as large-scale MSSP models grow in complexity, advanced decomposition techniques and machine-learning-based scenario generation could enhance tractability and scalability. Furthermore, applying the model to different geographical contexts with varying renewable-energy potentials, infrastructure capacities, and policy landscapes would test its generalizability and policy relevance. In summary, the proposed MSSP framework constitutes a significant step toward systematically designing robust and cost-effective RFSCs under uncertainty. By combining analytical rigor with policy insight, it establishes a strong foundation for future research and decision support in the sustainable energy transition.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used ChatGPT in order to improve the readability and language of the manuscript. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

CRediT authorship contribution statement

Mina Farajiamiri: Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Jörn-Christian Meyer:** Writing – review & editing, Supervision, Conceptualization. **Grit Walther:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

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

Acknowledgement

Funded by the Deutsche Forschungsgemeinschaft (DFG) under Germanýs Excellence Strategy – Cluster of Excellence 2186 "The Fuel Science Center" – ID: 390919832.

Support from Deutsche Forschungsgemeinschaft (DFG) within the project (ID: 516338899) IRTG 2983 Hy-Potential is gratefully acknowledged.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.compchemeng.2026.109779.

Appendix: Scenario Generation and Reduction Mechanics

To ensure reproducibility and provide a transparent view of the uncertainty modeling, this appendix details the mechanics of the scenario tree construction used in the case study.

Scenario Generation:

The future demand for renewable fuels (D^{χ}_{mt}) is modeled using a first-order autoregressive process (AR1). This approach ensures that demand scenarios exhibit realistic temporal dependencies, reverting to a projected mean trajectory while allowing for random, time-dependent shocks.

$$D^{\chi}_{mt} = \mu_{mt} + \rho_m \left(D^{\chi}_{m,t-1} - \mu_{m,t-1} \right) + \epsilon^{\chi}_{mt}$$

Mean Trajectory (μ_{mt}): The baseline projected demand for each fuel type (H_2, MeOH, NH_3, FT-fuels) is calibrated using reference datasets representing the expected market growth over the respective strategic time period. with the initial condition:

$$D^{\chi}_{m0} = \mu_{m0} = \mu_{m1}$$

Autoregressive Coefficient (ρ_m): The coefficient dictates the persistence of demand shocks from one period to the next. For this study, ρ_m is calibrated to 0.9 ($-1 < \rho_m < 1$) for all fuel types, indicating a high degree of temporal persistence where past deviations heavily influence the subsequent period's demand.

Error Term and Correlation (ϵ^{χ}_{mt}): The stochastic error terms are generated assuming a normal distribution $\epsilon^{\chi}_{mt} \sim N(0, \sigma^{\chi}_{m})$, where σ^{χ}_{m} represents the nominal standard deviation calibrated for each specific fuel. To construct the initial scenario fan of 300 scenarios, Latin Hypercube Sampling (LHS) is utilized. LHS guarantees a broader and more uniform coverage of the probability space compared to a standard Monte Carlo simulation (Govindan and Fattahi, 2017; Fattahi et al., 2015).

Independence Assumption: Regarding the correlation structure, the stochastic error terms are generated independently for each fuel type. No cross-correlation is applied among the different fuels. This modeling choice reflects the assumption that while the overall demand trajectories grow over time, the random market shocks affecting specific technological pathways, such as the adoption rate of hydrogen, are driven by isolated market dynamics, distinct technological breakthroughs, and specific policy incentives rather than a singular, perfectly correlated macroeconomic driver. Detailed values are provided in the supplementary material.

Scenario Reduction

Solving the MSSP over a 300-scenario fan across four strategic decades is computationally prohibitive. A forward-selection algorithm is applied to

compress the scenario fan into a computationally tractable tree while preserving the underlying statistical properties of the uncertainty space.

Distance Metric: The algorithm utilizes a probability-weighted Euclidean distance (Kantorovich distance (Römisch, 2003)) to measure the variance between scenarios at each time step. For any two scenarios, the distance is calculated across all fuel products and weighted by the probability of the corresponding scenario being merged.

Clustering and Branching: At each strategic node (t), scenarios exhibiting the lowest Kantorovich distance are iteratively merged. The branching structure (shown in Fig. 4) is governed by a dynamically decaying tolerance parameter.

$$\epsilon_t = \epsilon + \left[1 + q\left(1 - \frac{t}{T}\right)\right]$$

The baseline tolerance is set to $\epsilon = 2{,}900{,}000$ with a branching parameter of $q = 1$. This mathematical structure ensures that the tree branches out more densely in later periods where uncertainty is highest, while maintaining computational tractability in early stages.

Probability Redistribution: When a scenario is removed from the set, its discrete probability (π_χ) is added to its designated representative scenario to ensure $\sum \pi_\chi = 1$. This clustering process reduces the initial 300 scenarios to a final set of 15 representative scenarios at the terminal node.

Data availability

Research Link Provided

References

Renewables 2024 Global Status Report: Energy Demand, (2024). https://www.ren21.net/wp-content/uploads/2019/05/GSR2024_Demand_Full_Report.pdf?utm_source=chatgpt.com (accessed October 4, 2025).

A.M. Analytics, Methanol Analytics Report (Sample), (2024). https://www.argusmedia.com/-/media/project/argusmedia/mainsite/english/documents-and-files/brochures-and-downloads/2024/argus-methanol-analytics-report-sample-15-june-24-(1).pdf (accessed October 4, 2025).

Aboytes-Ojeda, M., Castillo-Villar, K.K., Eksioglu, S.D., 2019. Modeling and optimization of biomass quality variability for decision support systems in biomass supply chains. Ann. Oper. Res. 314, 319–346. https://doi.org/10.1007/s10479-019-03477-8.

S. Ahmed, A.J. King, G. Parija, A multi-stage stochastic integer programming approach for capacity expansion under uncertainty, 2003.

Albrecht, F.G., König, D.H., Baucks, N., Dietrich, R.U., 2017. A standardized methodology for the techno-economic evaluation of alternative fuels – a case study. Fuel 194, 511–526. https://doi.org/10.1016/j.fuel.2016.12.003.

Albrecht, F.G., Nguyen, T.V., 2020. Prospects of electrofuels to defossilize transportation in Denmark – a techno-economic and ecological analysis. Energy 192, 116511. https://doi.org/10.1016/j.energy.2019.116511.

Almansoori, A., Shah, N., 2012. Design and operation of a stochastic hydrogen supply chain network under demand uncertainty. Int. J. Hydrog. Energy 37, 3965–3977. https://doi.org/10.1016/j.ijhydene.2011.11.091.

Asadi, E., Habibi, F., Nickel, S., Sahebi, H., 2018. A bi-objective stochastic location-inventory-routing model for microalgae-based biofuel supply chain. Appl. Energy 228, 2235–2261. https://doi.org/10.1016/j.apenergy.2018.07.067.

Asche, F., Misund, B., Sikveland, M., 2013. The relationship between spot and contract gas prices in Europe. Energy Econ. 38, 212–217. https://doi.org/10.1016/j.eneco.2013.02.010.

Azizi, V., Hu, G., 2021. A multi-stage stochastic programming model for the multi-echelon multi-period reverse logistics problem. Sustainability 13. https://doi.org/10.3390/su132413596.

Babazadeh, R., Razmi, J., Pishvaee, M.S., Rabbani, M., 2017. A sustainable second-generation biodiesel supply chain network design problem under risk. Omega (U. K.) 66, 258–277. https://doi.org/10.1016/j.omega.2015.12.010.

Bairamzadeh, S., Saidi-Mehrabad, M., Pishvaee, M.S., 2018. Modelling different types of uncertainty in biofuel supply network design and planning: a robust optimization approach. Renew. Energy 116, 500–517. https://doi.org/10.1016/j.renene.2017.09.020.

Birge, J.R., 1982. The value of the stochastic solution in stochastic linear programs with fixed recourse. Math. Program. 24, 314–325. https://doi.org/10.1007/BF01585113.

J.R. Birge, F. Louveaux, Introduction to Stochastic Programming, Second, 2011a. https://doi.org/10.1007/978-1-4614-0237-4.

J.R. Birge, F. Louveaux, Introduction to Stochastic Programming, 2011b. https://doi.org/10.1007/978-1-4614-0237-4.

Brynolf, S., Taljegard, M., Grahn, M., Hansson, J., 2018. Electrofuels for the transport sector: a review of production costs. Renew. Sustain. Energy Rev. 81, 1887–1905. https://doi.org/10.1016/j.rser.2017.05.288.

Castillo-Villar, K.K., Eksioglu, S., Taherkhorsandi, M., 2017. Integrating biomass quality variability in stochastic supply chain modeling and optimization for large-scale biofuel production. J. Clean. Prod. 149, 904–918. https://doi.org/10.1016/j.jclepro.2017.02.123.

H.I. Cobuloglu, I.E. Büyüktahtakın, A two-stage stochastic mixed-integer programming approach to the competition of biofuel and food production, 2017. https://doi.org/10.1016/j.cie.2017.02.017.

Čuček, L., Martín, M., Grossmann, I.E., Kravanja, Z., 2014. Multi-period synthesis of optimally integrated biomass and bioenergy supply network. Comput. Chem. Eng. 66, 57–70. https://doi.org/10.1016/j.compchemeng.2014.02.020.

Dayhim, M., Jafari, M.A., Mazurek, M., 2014. Planning sustainable hydrogen supply chain infrastructure with uncertain demand. Int. J. Hydrog. Energy 39, 6789–6801. https://doi.org/10.1016/j.ijhydene.2014.02.132.

Delkhosh, F., Sadjadi, S.J., 2020. A robust optimization model for a biofuel supply chain under demand uncertainty. Int. J. Energy Environ. Eng. 11, 229–245. https://doi.org/10.1007/s40095-019-00329-w.

Dilaver, Z., Hunt, L.C., 2021. Modelling U.S. gasoline demand: a structural time series analysis with asymmetric price responses. Energy Policy 156. https://doi.org/10.1016/j.enpol.2021.112386.

Dupačová, J., 1995. Multistage stochastic programs: the state-of-the-art and selected bibliography. Kybernetika 31, 151–174.

Dupacova, J., Gröwe-Kuska, N., Römisch, W., 2003. Scenario reduction in stochastic programming an approach using probability metrics. Prof. Inf. 10, 36–38. https://doi.org/10.1076/epri.10.10.36.6816.

E. 2022 European Commission, Water resources: long-term annual average, (2022). https://data.europa.eu/data/datasets/ocghud9lo16m1j9flj9ba?locale=en (accessed November 20, 2022).

Ebadi Torkayesh, A., Hendiani, S., Walther, G., Venghaus, S., 2024. Fueling the future: overcoming the barriers to market development of renewable fuels in Germany using a novel analytical approach. Eur. J. Oper. Res. https://doi.org/10.1016/j.ejor.2024.02.039.

EEA, 2024. Transport and Mobility. European Environment Agency. https://www.eea.europa.eu/en/topics/in-depth/transport-and-mobility?activeTab=fa515f0c-9ab0-493c-b4cd-58a32dfaae0a (accessed January 20, 2025).

Efthymiadou, M.E., Charitopoulos, V.M., Papageorgiou, L.G., 2025. Optimization approach for hydrogen infrastructure planning under uncertainty. Ind. Eng. Chem. Res. 64, 7431–7451. https://doi.org/10.1021/acs.iecr.4c04211.

EurEau, The governance of water services in Europe - 2020 edition, 2020. chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/https://www.danva.dk/media/6995/2020-eureau-governance-web.pdf (accessed November 18, 2025).

European Commission Joint Research Centre, Enspreso - Biomass, (2019a). http://data.europa.eu/89h/74ed5a04-7d74-4807-9eab-b94774309d9f.

European Commission Joint Research Centre, ENSPRESO - SOLAR - PV and CSP, (2019b). https://data.jrc.ec.europa.eu/dataset/18eb348b-1420-46b6-978a-fe0b79e30ad3.

European Commission Joint Research Centre, ENSPRESO - WIND - ONSHORE and OFFSHORE, (2019c). http://data.europa.eu/89h/6d0774ec-4fe5-4ca3-8564-626f4927744e.

Farajiamiri, M., Meyer, J.C., Walther, G., 2023. Multi-objective optimization of renewable fuel supply chains regarding cost, land use, and water use. Appl. Energy 349. https://doi.org/10.1016/j.apenergy.2023.121652.

Fasihi, M., Bogdanov, D., Breyer, C., 2017. Long-term hydrocarbon trade options for the Maghreb region and Europe-renewable energy based synthetic fuels for a net zero emissions world. Sustainability 9. https://doi.org/10.3390/su9020306.

Fasihi, M., Efimova, O., Breyer, C., 2019. Techno-economic assessment of CO 2 direct air capture plants. J. Clean. Prod. 224, 957–980. https://doi.org/10.1016/j.jclepro.2019.03.086.

Fasihi, M., Weiss, R., Savolainen, J., Breyer, C., 2021. Global potential of green ammonia based on hybrid PV-wind power plants. Appl. Energy 294. https://doi.org/10.1016/j.apenergy.2020.116170.

Fattahi, M., Govindan, K., 2017. Integrated forward/reverse logistics network design under uncertainty with pricing for collection of used products. Ann. Oper. Res. 253, 193–225. https://doi.org/10.1007/s10479-016-2347-5.

Fattahi, M., Govindan, K., 2018. A multi-stage stochastic program for the sustainable design of biofuel supply chain networks under biomass supply uncertainty and disruption risk: a real-life case study. Transp. Res. Logist. Transp. Rev. 118, 534–567. https://doi.org/10.1016/j.tre.2018.08.008.

Fattahi, M., Govindan, K., Keyvanshokooh, E., 2017. Responsive and resilient supply chain network design under operational and disruption risks with delivery lead-time sensitive customers. Transp. Res. Logist. Transp. Rev. 101, 176–200. https://doi.org/10.1016/j.tre.2017.02.004.

Fattahi, M., Govindan, K., Keyvanshokooh, E., 2018. A multi-stage stochastic program for supply chain network redesign problem with price-dependent uncertain demands. Comput. Oper. Res. 100, 314–332. https://doi.org/10.1016/j.cor.2017.12.016.

Fattahi, M., Mahootchi, M., Moattar Husseini, S.M., Keyvanshokooh, E., Alborzi, F., 2015. Investigating replenishment policies for centralised and decentralised supply chains using stochastic programming approach. Int. J. Prod. Res. 53, 41–69. https://doi.org/10.1080/00207543.2014.922710.

H. Felfel, O. Ayadi, F. Masmoudi, A multi-site supply chain planning using multi-stage stochastic programming, multiphysics modelling and simulation for systems design and monitoring (2015) 189–198. https://doi.org/10.1007/978-3-319-14532-7.
FVV, Future Fuels Study IV: The Transformation of Mobility to the GHG-neutral Post-Fossil Age, Frankfurt am Main, 2021. https://www.fvv-net.de/fileadmin/Storys/020.50_Sechs_Thesen_zur_Klimaneutralitaet_des_europaeischen_Verkehrssektors/FVV_Future_Fuels_StudyIV_The_Transformation_of_Mobility_H1269_2021-10_EN.pdf.
Galimova, T., Ram, M., Bogdanov, D., Fasihi, M., Gulagi, A., Khalili, S., Breyer, C., 2023. Global trading of renewable electricity-based fuels and chemicals to enhance the energy transition across all sectors towards sustainability. Renew. Sustain. Energy Rev. 183. https://doi.org/10.1016/j.rser.2023.113420.
Ghelichi, Z., Saidi-Mehrabad, M., Pishvaee, M.S., 2018b. A stochastic programming approach toward optimal design and planning of an integrated green biodiesel supply chain network under uncertainty: a case study. Energy 156, 661–687. https://doi.org/10.1016/j.energy.2018.05.103.
Ghelichi, Z., Tajik, J., Pishvaee, M.S., 2018a. A novel robust optimization approach for an integrated municipal water distribution system design under uncertainty: a case study of Mashhad. Comput. Chem. Eng. 110, 13–34. https://doi.org/10.1016/j.compchemeng.2017.11.017.
Goh, M., Lim, J.Y.S., Meng, F., 2007. A stochastic model for risk management in global supply chain networks. Eur. J. Oper. Res. 182, 164–173. https://doi.org/10.1016/j.ejor.2006.08.028.
Gonela, V., Zhang, J., Osmani, A., Onyeaghala, R., 2015. Stochastic optimization of sustainable hybrid generation bioethanol supply chains. Transp. Res. Logist. Transp. Rev. 77, 1–28. https://doi.org/10.1016/j.tre.2015.02.008.
Govindan, K., Fattahi, M., 2017. Investigating risk and robustness measures for supply chain network design under demand uncertainty: a case study of glass supply chain. Int. J. Prod. Econ. 183, 680–699. https://doi.org/10.1016/j.ijpe.2015.09.033.
Govindan, K., Fattahi, M., Keyvanshokooh, E., 2017. Supply chain network design under uncertainty: a comprehensive review and future research directions. Eur. J. Oper. Res. 263, 108–141. https://doi.org/10.1016/j.ejor.2017.04.009.
Guo, C., Hu, H., Wang, S., Rodriguez, L.F., Ting, K.C., Lin, T., 2022. Multiperiod stochastic programming for biomass supply chain design under spatiotemporal variability of feedstock supply. Renew. Energy 186, 378–393. https://doi.org/10.1016/j.renene.2021.12.144.
Hafiz, F., Rodrigo de Queiroz, A., Fajri, P., Husain, I., 2019. Energy management and optimal storage sizing for a shared community: a multi-stage stochastic programming approach. Appl. Energy 236, 42–54. https://doi.org/10.1016/j.apenergy.2018.11.080.
Heitsch, H., Römisch, W., 2003. Scenario reduction algorithms in stochastic programming. Comput. Optim. Appl. 2, 187–206, 10.1023/A.
H. Heitsch, W. Römisch, Generation of multivariate scenario trees to model stochasticity in power management, 2005 IEEE Russia Power Tech, PowerTech (2005) 1–7. https://doi.org/10.1109/PTC.2005.4524696.
Heitsch, H., Römisch, W., 2007. A note on scenario reduction for two-stage stochastic programs. Oper. Res. Lett. 35, 731–738. https://doi.org/10.1016/j.orl.2006.12.008.
Heitsch, H., Römisch, W., 2009. Scenario tree reduction for multistage stochastic programs. Comput. Manag. Sci. 6, 117–133. https://doi.org/10.1007/s10287-008-0087-y.
Hendiani, S., Walther, G., 2023. Sustainability performance evaluation of renewable energy systems using a new multi-expert multi-criteria interval type-2 fuzzy distance to ideal solution approach. Appl. Energy 347, 121436. https://doi.org/10.1016/j.apenergy.2023.121436.
Hombach, L.E., Büsing, C., Walther, G., 2018. Robust and sustainable supply chains under market uncertainties and different risk attitudes – a case study of the German biodiesel market. Eur. J. Oper. Res. 269, 302–312. https://doi.org/10.1016/j.ejor.2017.07.015.
Hombach, L.E., Cambero, C., Sowlati, T., Walther, G., 2016. Optimal design of supply chains for second generation biofuels incorporating European biofuel regulations. J. Clean. Prod. 133, 565–575. https://doi.org/10.1016/j.jclepro.2016.05.107.
Hombach, L.E., Walther, G., 2015. Pareto-efficient legal regulation of the (bio)fuel market using a bi-objective optimization model. Eur. J. Oper. Res. 245, 286–295. https://doi.org/10.1016/j.ejor.2015.02.039.
Hu, S., Han, C., Dong, Z.S., Meng, L., 2019. A multi-stage stochastic programming model for relief distribution considering the state of road network. Transp. Res. B: Methodol. 123, 64–87. https://doi.org/10.1016/j.trb.2019.03.014.
Hu, Z., Hu, G., 2018. A multi-stage stochastic programming for lot-sizing and scheduling under demand uncertainty. Comput. Ind. Eng. 119, 157–166. https://doi.org/10.1016/j.cie.2018.03.033.
Huang, K., Ahmed, S., 2009. The value of multistage stochastic programming in capacity planning under uncertainty. Oper. Res. 57, 893–904. https://doi.org/10.1287/opre.1080.0623.
Huang, Y., Fan, Y., Chen, C.W., 2014. An integrated biofuel supply chain to cope with feedstock seasonality and uncertainty. Transp. Sci. 48, 540–554. https://doi.org/10.1287/trsc.2013.0498.
I. Energy Agency, Global Hydrogen Review 2024, 2024a. www.iea.org.
I. Energy Agency, Renewables 2024, 2024b. www.iea.org.
IEA, Renewables 2021 - Analysis and forecast to 2026, 2021. www.iea.org/t&c/.
IEA, IEA, 2022. Transport. IEA, Paris. License: CC BY 4.0 (2022). https://www.iea.org/reports/transport.
IRENA, WTO, Enabling global trade in renewable hydrogen and derivative commodities, Abu Dhabi and Geneva, 2024. https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2024/Nov/IRENA_WTO_Enabling_global_trade_renewable_hydrogen_2024.pdf (accessed November 18, 2025).
H. Iseri, F. Iseri, M. El-Halwagi, E. Iakovou, E. Pistikopoulos, An enhanced decision-making framework for designing renewable energy supply chains, lecture notes in networks and systems 1531 LNNS (2025b) 722–732. https://doi.org/10.1007/978-3-031-98304-7_78/FIGURES/5.
Iseri, H., Iseri, F., El-Halwagi, M., Iakovou, E., Pistikopoulos, E.N., 2025a. A multi-objective decision-making framework for renewable energy transportation. Int. J. Hydrog. Energy 166, 150789. https://doi.org/10.1016/J.IJHYDENE.2025.150789.
Jadidbonab, M., Babaei, E., Mohammadi-ivatloo, B., 2019. CVaR-constrained scheduling strategy for smart multi carrier energy hub considering demand response and compressed air energy storage. Energy 174, 1238–1250. https://doi.org/10.1016/j.energy.2019.02.048.
Kalhor, T., Sharifi, M., Mobli, H., 2022. A robust optimization approach for an integrated hybrid biodiesel and biomethane supply chain network design under uncertainty: case study. Int. J. Energy Environ. Eng. https://doi.org/10.1007/s40095-022-00513-5.
Kim, S., Lee, J.H., 2023. Multi-period design of hybrid microgrid under multi-timescale uncertainties. IFAC-PapersOnLine. Elsevier B.V., pp. 1449–1453. https://doi.org/10.1016/j.ifacol.2023.10.1827
Kim, S., Park, J., Chung, W., Adams, D., Lee, J.H., 2024. Techno-economic analysis for design and management of international green hydrogen supply chain under uncertainty: an integrated temporal planning approach. Energy Convers. Manag. 301. https://doi.org/10.1016/j.enconman.2023.118010.
Lara, C.L., Mallapragada, D.S., Papageorgiou, D.J., Venkatesh, A., Grossmann, I.E., 2018. Deterministic electric power infrastructure planning: mixed-integer programming model and nested decomposition algorithm. Eur. J. Oper. Res. 271, 1037–1054. https://doi.org/10.1016/j.ejor.2018.05.039.
Larson, E.D., Jin, H., Celik, F.E., 2009. Large-scale gasification-based coproduction of fuels and electricity from switchgrass. Biofuels Bioprod. Biorefining 3, 174–194. https://doi.org/10.1002/bbb.137.
Li, Qi., Hu, G., 2014. Supply chain design under uncertainty for advanced biofuel production based on bio-oil gasification. Energy 74, 576–584. https://doi.org/10.1016/j.energy.2014.07.023.
Li, X., Lu, S., Li, Z., Wang, Y., Zhu, L., 2022. Modeling and optimization of bioethanol production planning under hybrid uncertainty: a heuristic multi-stage stochastic programming approach. Energy 245, 123285. https://doi.org/10.1016/j.energy.2022.123285.
Li, Y.P., Huang, G.H., Nie, S.L., 2006. An interval-parameter multi-stage stochastic programming model for water resources management under uncertainty. Adv. Water Resour. 29, 776–789. https://doi.org/10.1016/j.advwatres.2005.07.008.
M.K. Lim, Y. Ouyang, Biofuel Supply Chain Network Design and Operations, 2016. https://doi.org/10.1007/978-3-319-30094-8_13.
Liu, Z., Wang, S., Ouyang, Y., 2017. Reliable biomass supply chain design under feedstock seasonality and probabilistic facility disruptions. Energies 10. https://doi.org/10.3390/en10111895.
Malladi, K.T., Sowlati, T., 2018. Biomass logistics: a review of important features, optimization modeling and the new trends. Renew. Sustain. Energy Rev. 94, 587–599. https://doi.org/10.1016/j.rser.2018.06.052.
Marufuzzaman, M., Ekşioğlu, S.D., 2017. Designing a reliable and dynamic multimodal transportation network for biofuel supply chains. Transp. Sci. 51, 494–517. https://doi.org/10.1287/trsc.2015.0632.
Marufuzzaman, M., Eksioglu, S.D., Li, X., Wang, J., 2014. Analyzing the impact of intermodal-related risk to the design and management of biofuel supply chain. Transp. Res. E Logist. Transp. Rev. 69, 122–145. https://doi.org/10.1016/j.tre.2014.06.008.
Matinrad, N., Roghanian, E., Rasi, Z., 2013. Supply chain network optimization: a review of classification, models, solution techniques and future research. Uncertain Supply Chain Manag. 1, 1–24. https://doi.org/10.5267/j.uscm.2013.05.003.
J.D.A. v. d.N. Maurice Vos, Study on the Import of Liquid Renewable Energy: Technology Cost Assessment, Dnv Gl (2020). https://www.gie.eu/publications/studies/.
D.L. McCollum, J.M. Ogden, Techno-economic models for carbon dioxide compression, transport, and storage, 2006. http://escholarship.org/uc/item/1zg00532.pdf%5Cn/Users/mohammadmohammadi/Documents/Dropbox/Private/Research/CO2-Selected/mostimportantone/2006_UCD-ITS-RR-06-14.pdf.
Melo, M.T., Nickel, S., Saldanha-da-Gama, F., 2009. Facility location and supply chain management - A review. Eur. J. Oper. Res. 196, 401–412. https://doi.org/10.1016/j.ejor.2008.05.007.
Memişoğlu, G., Üster, H., 2021. Design of a biofuel supply network under stochastic and price-dependent biomass availability. IISE Trans. 53, 869–882. https://doi.org/10.1080/24725854.2020.1869870.
Mitrai, I., Palys, M.J., Daoutidis, P., 2026. A multistage stochastic programming approach for renewable ammonia supply chain network design. Comput. Chem. Eng. 205, 109443. https://doi.org/10.1016/j.compchemeng.2025.109443.
Moustakas, K., Loizidou, M., Rehan, M., Nizami, A.S., 2020. A review of recent developments in renewable and sustainable energy systems: key challenges and future perspective. Renew. Sustain. Energy Rev. 119. https://doi.org/10.1016/j.rser.2019.109418.
Nichol, H., Adams, M., Nyathi, J., Sood, S., Davies, A., Hart, R., MacLean, G., 2023. Weighing the EU's Options: Importing vs Domestic Production of Hydrogen/E-Fuels. Oxfordshire. www.ricardo.com.
Nickel, S., Saldanha-da-Gama, F., Ziegler, H.P., 2012. A multi-stage stochastic supply network design problem with financial decisions and risk management. Omega 40, 511–524. https://doi.org/10.1016/j.omega.2011.09.006.
Nunes, P., Oliveira, F., Hamacher, S., Almansoori, A., 2015. Design of a hydrogen supply chain with uncertainty. Int J. Hydrog. Energy 40, 16408–16418. https://doi.org/10.1016/j.ijhydene.2015.10.015.

Nur, F., Aboytes-Ojeda, M., Castillo-Villar, K.K., Marufuzzaman, M., 2021. A two-stage stochastic programming model for biofuel supply chain network design with biomass quality implications. IISE Trans. 53, 845–868. https://doi.org/10.1080/24725854.2020.1751347.

O'Neill, E.G., Martinez-Feria, R.A., Basso, B., Maravelias, C.T., 2022. Integrated spatially explicit landscape and cellulosic biofuel supply chain optimization under biomass yield uncertainty. Comput. Chem. Eng. 160, 107724. https://doi.org/10.1016/j.compchemeng.2022.107724.

Osmani, A., Zhang, J., 2013. Stochastic optimization of a multi-feedstock lignocellulosic-based bioethanol supply chain under multiple uncertainties. Energy 59, 157–172. https://doi.org/10.1016/j.energy.2013.07.043.

Osmani, A., Zhang, J., 2014. Economic and environmental optimization of a large scale sustainable dual feedstock lignocellulosic-based bioethanol supply chain in a stochastic environment. Appl. Energy 114, 572–587. https://doi.org/10.1016/j.apenergy.2013.10.024.

Osmani, A., Zhang, J., 2017. Multi-period stochastic optimization of a sustainable multi-feedstock second generation bioethanol supply chain – a logistic case study in Midwestern United States. Land Use Policy 61, 420–450. https://doi.org/10.1016/j.landusepol.2016.10.028.

Pfenninger, S., Staffell, I., 2016. Long-term patterns of European PV output using 30 years of validated hourly reanalysis and satellite data. Energy 114, 1251–1265. https://doi.org/10.1016/j.energy.2016.08.060.

Pimentel, B.S., Mateus, G.R., Almeida, F.A., 2013. Stochastic capacity planning and dynamic network design. Int. J. Prod. Econ. 145, 139–149. https://doi.org/10.1016/j.ijpe.2013.01.019.

M.S. Pishvaee, S. Mohseni, S. Bairamzadeh, Biomass to biofuel supply chain design and planning under uncertainty concepts and quantitative methods, 2020.

Poudel, S., Marufuzzaman, M., Bian, L., 2016. Designing a reliable bio-fuel supply chain network considering link failure probabilities. Comput. Ind. Eng. 91, 85–99. https://doi.org/10.1016/j.cie.2015.11.002.

Poudel, Sushil., Marufuzzaman, M., Quddus, M.A., Chowdhury, S., Bian, L., Smith, B., 2018. Designing a reliable and congested multi-modal facility location problem for biofuel supply chain network. Energies 11. https://doi.org/10.3390/en11071682.

Pourhejazy, P., Kwon, O.K., 2016. The new generation of operations research methods in supply chain optimization: a review. Sustainability 8. https://doi.org/10.3390/su8101033.

Quarton, C.J., Samsatli, S., 2020. The value of hydrogen and carbon capture, storage and utilisation in decarbonising energy: insights from integrated value chain optimisation. Appl. Energy 257, 113936. https://doi.org/10.1016/j.apenergy.2019.113936.

Quddus, M.A., Chowdhury, S., Marufuzzaman, M., Yu, F., Bian, L., 2018. A two-stage chance-constrained stochastic programming model for a bio-fuel supply chain network. Int. J. Prod. Econ. 195, 27–44. https://doi.org/10.1016/j.ijpe.2017.09.019.

Quddus, M.A., Ibne Hossain, N.U., Mohammad, M., Jaradat, R.M., Roni, M.S., 2017. Sustainable network design for multi-purpose pellet processing depots under biomass supply uncertainty. Comput. Ind. Eng. 110, 462–483. https://doi.org/10.1016/j.cie.2017.06.001.

S. Rachev, L. Rüschendorf, Mass transportation problems, 1998. https://doi.org/10.1007/b98894.

Raya-Tapia, A.Y., López-Flores, F.J., Sánchez, A., Martín, M., Ramírez-Márquez, C., Ponce-Ortega, J.M., 2025. Power-to-X and the green chemical revolution: a review on sustainable energy carriers and synthetic fuels. Ind. Eng. Chem. Res. 64, 20379–20403. https://doi.org/10.1021/acs.iecr.5c02274.

Renewables.ninja, (2016). https://www.renewables.ninja/ (accessed October 19, 2025).

Reuß, M., Grube, T., Robinius, M., Preuster, P., Wasserscheid, P., Stolten, D., 2017. Seasonal storage and alternative carriers: a flexible hydrogen supply chain model. Appl. Energy 200, 290–302. https://doi.org/10.1016/j.apenergy.2017.05.050.

Werner. Römisch, Stability of stochastic programming problems, handbooks in operations research and management science 10 (2003) 483–554. https://doi.org/10.1016/S0927-0507(03)10008-4.

Römisch, Werner., Wets, R.J.B., 2007. Stability of ε-approximate solutions to convex stochastic programs. SIAM J. Optim. 18, 961–979. https://doi.org/10.1137/060657716.

Samsatli, S., Samsatli, N.J., 2018. A multi-objective MILP model for the design and operation of future integrated multi-vector energy networks capturing detailed spatio-temporal dependencies. Appl. Energy 220, 893–920. https://doi.org/10.1016/j.apenergy.2017.09.055.

Samsatli, S., Samsatli, N.J., Shah, N., 2015. BVCM: a comprehensive and flexible toolkit for whole system biomass value chain analysis and optimisation - mathematical formulation. Appl. Energy 147, 131–160. https://doi.org/10.1016/j.apenergy.2015.01.078.

Shin, W., Lee, Y., Yu, Y., Song, H.H., 2025. Optimization of emission-based sliding-premium incentive policy for clean energy market: a case study of clean hydrogen producers and importers. Appl. Energy 390. https://doi.org/10.1016/j.apenergy.2025.125710.

Shuai, C., Shen, L., Jiao, L., Wu, Y., Tan, Y., 2024. Effective hydrogen supply chain management framework considering nonlinear multi-stage process uncertainties. Appl. Energy 367, 123328. https://doi.org/10.1016/j.apenergy.2016.11.029.

Sodhi, M.M.S., 2005. Managing demand risk in tactical supply chain planning for a global consumer electronics company. Prod. Oper. Manag. 14, 69–79. https://doi.org/10.1111/j.1937-5956.2005.tb00010.x.

Staffell, I., Pfenninger, S., 2016. Using bias-corrected reanalysis to simulate current and future wind power output. Energy 114, 1224–1239. https://doi.org/10.1016/j.energy.2016.08.068.

Sun, F., Aguayo, M.M., Ramachandran, R., Sarin, S.C., 2018. Biomass feedstock supply chain design–a taxonomic review and a decomposition-based methodology. Int. J. Prod. Res. 56, 5626–5659. https://doi.org/10.1080/00207543.2018.1475766.

Varone, A., Ferrari, M., 2015. Power to liquid and power to gas: an option for the German Energiewende. Renew. Sustain. Energy Rev. 45, 207–218. https://doi.org/10.1016/j.rser.2015.01.049.

Vo, D.N., Zhang, X., Yin, X., 2025. Forecasting and surrogate models-based MINLP for long-term integrated design and planning of power-to-methanol. Appl. Energy 397. https://doi.org/10.1016/j.apenergy.2025.126336.

A. Wang, J. Jens, D. Mavins, M. Moultak, M. Schimmel, K. Van Der Leun, D. Peters, M. Buseman, Analysing future demand, supply, and transport of hydrogen, European hydrogen backbone (2021) 70.

A. Wang, K. van der Leun, D. Peters, M. Buseman, European Hydrogen Backbone - https://transparency.entsog.eu/, (2020) 24.

Wang, B., Wang, X., Wei, F., Shao, C., Zhou, J., Lin, J., 2023. Multi-stage stochastic planning for a long-term low-carbon transition of island power system considering carbon price uncertainty and offshore wind power. Energy 282. https://doi.org/10.1016/j.energy.2023.128349.

T. Wang, R. De Neufville, Building real options into physical systems with stochastic mixed-integer programming, 8th Real Options Annual International Conference (2004) 1–35.

Wolff, M., Becker, T., Walther, G., 2023. Long-term design and analysis of renewable fuel supply chains – an integrated approach considering seasonal resource availability. Eur. J. Oper. Res. 304, 745–762. https://doi.org/10.1016/j.ejor.2022.04.001.

Xie, F., Huang, Y., 2018. A multistage stochastic programming model for a multi-period strategic expansion of biofuel supply chain under evolving uncertainties. Transp. Res. E Logist. Transp. Rev. 111, 130–148. https://doi.org/10.1016/j.tre.2018.01.015.

Xie, F., Huang, Y., Eksioglu, S., 2014. Integrating multimodal transport into cellulosic biofuel supply chain design under feedstock seasonality with a case study based on California. Bioresour. Technol. 152, 15–23. https://doi.org/10.1016/j.biortech.2013.10.074.

Yu, J., Lee, I.B., Han, J., Ahn, Y., 2020. Stochastic approach to optimize the supply chain network of microalga-derived biodiesel under uncertain diesel demand. J. Chem. Eng. Jpn. 53, 24–35. https://doi.org/10.1252/jcej.19we110.

Yue, D., You, F., Snyder, S.W., 2014. Biomass-to-bioenergy and biofuel supply chain optimization: overview, key issues and challenges. Comput. Chem. Eng. 66, 36–56. https://doi.org/10.1016/j.compchemeng.2013.11.016.

Zandi Atashbar, N., Labadie, N., Prins, C., 2018. Modelling and optimisation of biomass supply chains: a review. Int. J. Prod. Res. 56, 3482–3506. https://doi.org/10.1080/00207543.2017.1343506.

Zarei, M., Shams, M.H., Niaz, H., Won, W., Lee, C.J., Liu, J.J., 2022. Risk-based multistage stochastic mixed-integer optimization for biofuel supply chain management under multiple uncertainties. Renew. Energy 200, 694–705. https://doi.org/10.1016/j.renene.2022.10.003.

Zhang, F., Guo, P., Engel, B.A., Guo, S., Zhang, C., Tang, Y., 2019. Planning seasonal irrigation water allocation based on an interval multiobjective multi-stage stochastic programming approach. Agric. Water Manag. 223, 105692. https://doi.org/10.1016/j.agwat.2019.105692.

J. Zhang, A. Osmani, Economic and land-use optimization of lignocellulosic-based bioethanol supply chains under stochastic environment, 2015. https://doi.org/10.1007/978-3-319-20092-7_9.

Zhou, Y., Huang, G.H., Yang, B., 2013. Water resources management under multi-parameter interactions: a factorial multi-stage stochastic programming approach. Omega (U. K.) 41, 559–573. https://doi.org/10.1016/j.omega.2012.07.005.

Zimberg, B., Testuri, C.E., Ferrari, G., 2019. Stochastic modeling of fuel procurement for electricity generation with contractual terms and logistics constraints. Comput. Chem. Eng. 123, 49–63. https://doi.org/10.1016/j.compchemeng.2018.12.021.