Optimizing Renewable Fuel Supply Chain Network Design Under Sustainability and Uncertainty Considerations

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Mina Farajiamiri

Berichterin: Univ.-Prof. Dr. rer. pol. Grit Walther

Berichterin: Univ.-Prof. Dr. rer. pol. Sandra Venghaus

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I hope the insights of this work contribute, even in a small way, to advancing a better and more sustainable future for all.

“That which cannot be measured cannot be improved.” — Al-Khwarizmi

Abstract

This dissertation develops an integrated decision-support framework for the design of renewable fuel supply chains that support decarbonization of hard-to-electrify transport sectors under stringent sustainability constraints and pervasive uncertainty. Motivated by the need to align large-scale fuel production with climate targets, limited land and water resources, and existing uncertainties, the work addresses four overarching research questions: (i) can economic, land use, and water use trade-offs in EU-wide renewable fuel supply chains be quantified and optimized; (ii) how does variability in renewable electricity sources affect optimal infrastructure and import strategies; (iii) how can advanced uncertainty-aware planning approaches support adaptive, time-dependent decision-making along evolving fuel-demand trajectories; and (iv) what combined insights emerge from integrating sustainability and uncertainty modeling for EU-level planning and policy.

Methodologically, the dissertation builds a flexible strategic–tactical mixed-integer linear programming framework based on a Resource–Technology–Network representation for multi-period, multi-feedstock, multi-product renewable fuel supply chains producing Fischer–Tropsch fuels, methanol, hydrogen, and ammonia from biomass, CO_2, and renewable electricity. Environmental sustainability is captured by extending the economic objective with explicit land use and water use objectives, which are jointly optimized using the augmented ε-constraint method to generate Pareto-efficient frontiers. Tactical uncertainty in renewable electricity availability is represented through a two-stage stochastic programming model that links long-term investment decisions with tactical recourse and distinguishes between contracted and spot imports; renewable electricity variability is captured via scenario trees derived from multi-decadal capacity factor data. Strategic, time-dependent demand uncertainty is addressed through a multi-stage stochastic programming model that employs autoregressive demand processes and forward scenario reduction to construct tractable scenario trees, enabling sequential infrastructure adaptation under non-anticipativity constraints. All models are applied to an EU+UK case study for transport fuel demand over 2021–2060.

The results demonstrate that no single renewable fuel supply chain configuration simultaneously minimizes cost, land, and water use, but that substantial environmental improvements can be achieved at moderate cost premiums. The multi-objective analysis reveals dense Pareto fronts and a compromise solution in which large reductions in land and water requirements are

attainable with relatively small increases in total system cost, while cost-optimal pathways are dominated by renewable electricity–based technologies and rely structurally on imports. The two-stage stochastic programming results show that explicitly modeling renewable electricity variability induces more flexible yet robust infrastructure portfolios, with strong regional specialization in solar and wind deployment, late but significant uptake of contracted imports, and measurable economic benefits compared with deterministic planning. The multi-stage stochastic programming analysis highlights adaptive investment paths that hedge through early diversification and converge as information is revealed, quantifying the economic penalty of demand uncertainty and the cost savings from multi-stage planning relative to static designs. Together, the three papers provide a coherent, quantitative basis for designing renewable fuel supply chains that jointly balance economic efficiency, land and water constraints, and robustness to both supply-side and demand-side uncertainties, yielding policy-relevant insights on technology portfolios, infrastructure timing, and the long-term role of imports in EU renewable fuel strategies.

Zusammenfassung

Diese Dissertation entwickelt einen integriereten Modellierungs- und Entscheidungsansatz zur Auslegung erneuerbarer Kraftstoff-Lieferketten, dass die Dekarbonisierung schwer zu elektrifizierender Verkehrssektoren unter strengen Nachhaltigkeitsvorgaben und allgegenwärtiger Unsicherheit unterstützt. Die Auslegung großskaliger Lieferketten für erneuerbare Kraftstoffe ist mit Zielkonflikten zwischen Klimazielen, begrenzten Land- und Wasserressourcen sowie erheblichen Unsicherheiten verbunden. Daraus ergeben sich vier übergeordnete Forschungsfragen: (i) wie lassen sich ökonomische, flächenbezogene und wasserbezogene Zielkonflikte in EU-weiten Lieferketten für erneuerbare Kraftstoffe quantifizieren und optimieren; (ii) wie beeinflusst die Variabilität erneuerbarer Stromquellen die optimale Infrastruktur- und Importstrategie; (iii) wie Entscheidungsansätze unter Unsicherheit eine adaptive, zeitabhängige Planung entlang unsicherer Kraftstoffnachfrageverläufe verbessern können; und (iv) welche kombinierten Erkenntnisse sich aus der integrierten Modellierung von Nachhaltigkeit und Unsicherheit für EU-weite Planung und Politik ableiten lassen.

Methodisch basiert die Dissertation auf einem flexiblen strategisch–taktischen Mixed-Integer-Linear-Programming-Framework mit einer Resource–Technology–Network-Repräsentation für mehrperiodige, multifunktionale Lieferketten zur Herstellung von Fischer-Tropsch-Kraftstoffen, Methanol, Wasserstoff und Ammoniak aus Biomasse, CO_2 und erneuerbarem Strom. Ökologische Nachhaltigkeit wird abgebildet. Die ökonomische Zielfunktion wird um explizite Zielfunktionen für den Flächen- und Wasserverbrauch ergänzt. Diese Zielfunktionen werden im Rahmen eines multiobjektiven Optimierungsansatzes mithilfe des Augmented-ε-Constraint-Verfahrens gemeinsam optimiert, um Pareto-effiziente Lösungsfronten zu bestimmen.

Taktische Unsicherheiten in der Verfügbarkeit erneuerbarer Elektrizität werden mithilfe eines zweistufigen stochastischen Programmierungsmodell abgebildet, das langfristige Investitionsentscheidungen mit taktischen Rekursentscheidungen verknüpft und zwischen kontrahierten und Spot-Importen unterscheidet. Die zeitliche Variabilität erneuerbaren Stroms wird über Szenariobäume modelliert, die aus mehrdekadischen Kapazitätsfaktor-Daten abgeleitet sind. Strategische, zeitabhängige Unsicherheiten der Kraftstoffnachfrage werden durch ein mehrstufiges stochastisches Programmierungsmodell erfasst, das autoregressive Nachfrageprozesse und Forward-Szenarioreduktion zur Konstruktion handhabbarer Szenariobäume nutzt

und damit eine sequenzielle Anpassung der Infrastruktur unter Nicht-Antizipations-Nebenbedingungen ermöglicht. Alle Modelle werden auf eine EU+UK-Fallstudie zur Verkehrskraftstoffnachfrage im Zeitraum von 2021 bis 2060 angewendet.

Die Ergebnisse zeigen, dass keine einzelne Konfiguration der Lieferkette für erneuerbare Kraftstoffe gleichzeitig Kosten, Flächen- und Wasserverbrauch minimiert, dass jedoch erhebliche Umweltverbesserungen bei moderaten Kostenaufschlägen erreichbar sind. Die Mehrzieloptimierung ergibt dichte Pareto-Fronten und eine Kompromisslösung, bei der große Reduktionen des Flächen- und Wasserbedarfs mit relativ geringen Erhöhungen der Gesamtsystemkosten realisiert werden können, während kostenoptimale Pfade von strombasierter Technologie geprägt sind und strukturell auf Importe angewiesen bleiben. Die Ergebnisse der zweistufigen stochastischen Programmierung zeigen, dass die Modellierung der Variabilität erneuerbaren Stroms zu flexibleren und zugleich robusteren Infrastrukturportfolios führt, mit starker regionaler Spezialisierung beim Ausbau von Solar- und Windenergie, einer späten, aber substanziellen Aufnahme vertragsbasierten Importe sowie messbaren ökonomischen Vorteilen gegenüber deterministischer Planung. Die mehrstufige stochastische Programmierung macht anpassungsfähige Investitionspfade sichtbar, die zunächst durch frühe Diversifikation abgesichert sind und mit zunehmender Informationsauflösung konvergieren. Zudem werden die ökonomischen Kosten der Nachfrageunsicherheit sowie die Kosteneinsparungen mehrstufiger Planung gegenüber statischen Designs quantifiziert. Insgesamt liefern die drei Arbeiten eine kohärente, quantitative Grundlage für die Auslegung erneuerbarer Kraftstoff-Lieferketten, in der ökonomische Effizienz, Flächen- und Wasserrestriktionen sowie Robustheit gegenüber angebots- und nachfrageseitigen Unsicherheiten gemeinsam berücksichtigt werden. Daraus ergeben sich politikrelevante Erkenntnisse zu Technologieportfolios, zum zeitlichen Ausbau von Infrastruktur und zur langfristigen Rolle von Importen in EU-Strategien für erneuerbare Kraftstoffe.

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ABBREVIATIONS

AEL Alkaline Electrolyzer

ASU Air Separation Unit

AUGMECON Augmented ε-constraint method

BtL Biomass-to-Liquid

CAPEX Capital Expenditures

CCUS Carbon Capture, Utilization, and Storage

CO_2 Carbon Dioxide

CP Capacity Planning

DAC Direct Air Capture

DME Dimethylether

DQN Deep Q-Network

EEV Expected Result of Expected Value

ETC Expected Total Cost

EU European Union

EV Expected Value

EVPI Expected Value of Perfect Information

FT Fischer-Tropsch

GHG Greenhouse gas

GWP Global Warming Potential

H_2 Hydrogen

LCA Life Cycle Assessment

LCO Life Cycle Optimization

LHS Latin Hypercube Sampling

LHV Lower Heating Value

LUC Land Use Change

MC Multi-Commodity

MeOH Methanol

MILP Mixed-Integer Linear Programming

MINLP Mixed-Integer Nonlinear Programming

MP Multi-Product

MR Multi-Resource

MSSP Multi-Stage Stochastic Programming

N_2 Nitrogen

NH_3 Ammonia

NPV Net Present Value

O&M Operation and Maintenance

OMEn Oxymethylene-ether

OPEX Operational Expenditures

PBtL Power-Biomass-to-Liquid

PEM Proton Exchange Membrane

PPF Percent Point Function

PtL Power-to-Liquid

PV Photovoltaics (Solar)

RES Renewable Electricity Sources

RFSC Renewable Fuel Supply Chain

RHS Right Hand Side

RQ Research Questions

RTN Resource–Technology–Network

RVMSS Relative Value of Multi-Stage Stochastic Solution

SAF Sustainable Aviation Fuels

SC Supply Chain

SCND Supply Chain Network Design

SP Stochastic Programming

SR Single-Resource

TSSP Two-Stage Stochastic Programming

UK United Kingdom

US United States

VSS Value of Stochastic Solution

WP Wind Power

WRM Water Resources Management

WS Wait-and-See

PART I: PREFACE

Chapter 1

1 Introduction

This opening chapter lays the groundwork for the subsequent investigation of renewable fuel supply chains (RFSCs) design. Section 1.1 provides the necessary background, situating the research within broader literature and outlining the motivation for designing RFSCs. Section 1.2 then presents the dissertation's objectives and structure, offering a clear roadmap to guide readers through the chapters that follow.

1.1 Background

Mitigating climate change and limiting global warming to well below 2 °C requires substantial reductions in CO_2 and other greenhouse gas emissions across all sectors (Nations Unies, 2015). The transportation sector plays a central role in this regard. In 2018, fossil fuel combustion in transport accounted for 23% of global emissions, with levels rising steadily since 2000, except for the temporary COVID-19 decline (IEA, 2022). In the European Union (EU), the transport sector was responsible for 29% of total greenhouse gas emissions in 2022 (EEA, 2024). With global passenger and freight activity projected to increase further, defossilizing the transport sector is essential to achieving climate neutrality (EEA, 2022).

While electrification is highly effective for light-duty vehicles, battery-electric propulsion remains technically and economically constrained for heavy-duty road transport, aviation, and maritime shipping (DNV, 2023). These hard-to-electrify sectors will continue to require dense, energy-rich fuels, meaning that liquid fuels, particularly renewable ones, will remain essential for decades to come (Fasihi et al., 2017). Renewable hydrocarbon "drop-in" fuels such as methanol (MeOH), ethanol, Dimethylether (DME), Oxymethylene-ether (OMEn), and Fischer–Tropsch (FT) fuels can be used within existing vehicle fleets and distribution infrastructure, enabling immediate emission reductions without major system modifications (Dry, 2002). More broadly, renewable fuels complement electrification and form a critical pillar of decarbonization strategies in heavy-duty transport (IEA, 2022). The advantages of renewables for fuel production are increasingly evident. Between 2005 and 2020, the share of renewable energy in EU transport grew from under 2% to 10.2% (EEA, 2021).

A diverse portfolio of renewable fuels has emerged to support decarbonization. FT-fuels can be blended at high ratios with fossil fuels, making them attractive "drop-in" options that facilitate market penetration (Schemme et al., 2017). Hydrogen (H_2) is increasingly viewed as a key energy carrier across electricity, heat, industry, transport, and storage applications (Abdin et al., 2020), with large production increases expected globally (Wang et al., 2021). Renewable MeOH offers high energy density, safe handling, and compatibility with existing infrastructure, making it an attractive long-term transport fuel (Olah, 2005). Both MeOH and H_2 are also promising carriers for storing fluctuating renewable electricity (Bos et al., 2020; Yan et al., 2020). Green ammonia (NH_3) is gaining momentum as a renewable fuel due to its carbon-free combustion, established production pathways, and suitability for long-distance energy transport. (DNV GL - Maritime, 2019; Sagel et al., 2022; Xing et al., 2021). However, its toxicity and the industrial orientation of existing infrastructure require major investments, regulatory adaptations, and safety measures for large-scale deployment (Nicola Jones, 2022).

Renewable fuels can be produced via multiple thermochemical and biochemical pathways, each differing in feedstock availability, conversion efficiencies, infrastructural needs, and cost structures. When powered by renewable electricity, these fuels provide climate-compatible alternatives to fossil liquids, help meet rising transport demand, enhance energy security, and mitigate renewable-generation intermittency through chemical energy storage (Liebich et al., 2021). Their production relies primarily on renewable electricity, water, and carbon inputs (Albrecht & Nguyen, 2020), and their regional viability varies markedly due to heterogeneous resource potentials (Teske et al., 2021).

However, effectively developing and scaling renewable fuels depends on well-designed supply chains (SCs), capable of integrating diverse feedstocks, processes, technologies, and facilities. These SCs must balance domestic production with imports, accommodate long-term demand evolution, manage seasonal variability, and coordinate investments across generation, conversion, storage, and distribution (Wolff et al., 2023).

Designing RFSCs is complicated by long infrastructure lifetimes and various uncertainties about future energy systems in net-zero pathways. Achieving climate neutrality demands coordinated, multi-decadal planning of production, storage, and distribution assets that must adapt to evolving policies, technology learning, and global resource competition. This long-term outlook heightens the risk of stranded assets, underscoring the need for flexible, robust

system configurations that remain viable under diverse future conditions (Firdaus & Mori, 2023).

Moreover, resource-constrained regions like the EU will rely structurally on imports, making it a core element of future renewable fuel systems (Giannelos et al., 2021; Vos et al., 2020; Nichol et al., 2023). Long-term import contracts offer stability, while spot imports provide flexibility but at higher or more volatile prices. Capturing both mechanisms is crucial for robust SC design (Galimova et al., 2023).

Renewable fuels must be evaluated not only for their climate-mitigation potential but also for their broader sustainability impacts. Expanding renewable fuel pathways can intensify competition for land and water, influence biodiversity and food systems, and place additional pressures on local ecosystems, while their production requires materials, energy, and infrastructure with associated environmental footprints. A holistic assessment is therefore essential to ensure renewable fuels support both emissions reduction and long-term environmental sustainability (IEA Bioenergy, 2023; Jeswani et al., 2020).

Decarbonization implies a major expansion in renewable energy, which will reshape global land and water use as policies evolve (Enserink et al., 2022). Land is increasingly contested among agriculture, forestry, conservation, human settlement, and energy infrastructure; although current energy systems occupy only about 0.4% of global land, solar, wind, hydro, and biomass have much lower energy densities than fossil resources and thus require substantially more land per unit of energy produced (Capellán-Pérez et al., 2017; Lovering et al., 2022).

Water availability is equally important. Agriculture already accounts for roughly 86% of global freshwater use, and renewable fuels create additional competition through biomass irrigation and water demand for H_2 production, even though solar, wind, and geothermal generally have low water intensities (Hoekstra & Chapagain, 2006; Howells et al., 2013). Land and water availability, therefore, emerge as critical constraints for RFSC design.

While sustainability constraints shape the feasibility of renewable fuel pathways, their long-term development is further complicated by substantial uncertainty across supply, demand, and technology, which can significantly affect both the viability and optimality of SCs. RFSCs face multiple layers of uncertainty.

On the supply side, resource availability varies due to seasonality, feedstock competition, and evolving resource potentials (Poudel et al., 2016). Production technologies such as elec-

trolysis and DAC exhibit uncertain cost trajectories and scalability (Yue et al., 2014), and infrastructure investments involve long asset lifetimes, creating high exposure to future uncertainty (Xie & Huang, 2018; Zarei et al., 2022). Deterministic models, though common, often yield infeasible or suboptimal results when real conditions deviate from assumed averages (Huang et al., 2014). Ignoring uncertainty can lead to underinvestment in flexibility, misallocation of resources, and ill-preparedness for extreme conditions, whereas stochastic modeling enables decision-makers to account for variability, explore strategy robustness, and design SCs that perform reliably across a wide range of possible futures (Bairamzadeh et al., 2018; Habibi et al., 2023).

Demand for renewable fuels depends heavily on evolving policies, market competition, technology adoption, consumer preferences, and economic conditions, leading to divergent projections and structural shifts that make long-term demand highly uncertain (IEA, 2021; Moustakas et al., 2020). Additional uncertainty in renewable fuels stems from renewable electricity availability, which directly affects the cost and production of H_2 and synthetic hydrocarbons. Solar and wind exhibit strong temporal and spatial variability, yet many SC network design models still rely on deterministic averages (Carreras et al., 2021; Demirhan et al., 2020; Denholm et al., 2013). Explicitly modeling these uncertainties can uncover different infrastructure priorities, highlight storage needs, and reveal trade-offs between domestic production and imports. Overall, addressing uncertainty is therefore essential for designing robust, flexible, and adaptive RFSCs.

1.2 Aim and structure

Against this background, the main aim of this dissertation is to provide decision support for designing cost-efficient, robust, and sustainable RFSCs under long-term uncertainty. The work seeks to generate new insights into how renewable fuels can be produced, supplied, and deployed in line with climate targets while accounting for regional and temporal resource constraints, technological diversity, and evolving demand. Several research questions (RQs) arise from this objective.

RQ1: How can renewable fuel supply chains be designed and optimized regarding economic, land use, and water use objective functions?

RQ1 examines how RFSCs can be designed to achieve economic efficiency while meeting broader sustainability goals, including key environmental considerations. As large-scale deployment affects land and water resources, this question focuses on the trade-offs among

costs, land use, and water use. It aims to identify system configurations that remain feasible and sustainable when multiple objective functions must be considered simultaneously. RQ1 is addressed primarily in Research Paper 1, which develops the multi-objective framework for the minimization of total system cost, land use, and water use in EU-wide RFSC modeling.

RQ2: How does uncertainty in renewable electricity sources affect optimal infrastructure and sourcing strategies for renewable fuel supply chains?

RQ2 examines how variability in renewable electricity availability influences RFSC design. Because wind and solar resources fluctuate over time and across regions, production levels and infrastructure needs are inherently uncertain. Therefore, RQ2 explores how SCs can be planned to remain cost-effective and flexible despite uncertain renewable energy inputs. RQ2 is mainly addressed in Research Paper 2, which develops a Two-Stage Stochastic Programming (TSSP) framework to capture uncertainty in renewable electricity sources (RES) availability in the EU-wide RFSC model.

RQ3: How can uncertainty-aware planning approaches support adaptive, time-dependent decision-making under uncertain demand trajectories for renewable fuels?

RQ3 addresses the uncertainty in future demand for renewable fuels, which depends on evolving technologies, policies, and market developments. Since infrastructure investments last for decades, planning must adapt to multiple possible demand trajectories. This question focuses on how sequential, time-dependent decision-making can enhance flexibility and ensure that SCs remain viable under shifting demand conditions. Research Paper 3 focuses primarily on RQ3 and develops the Multi-Stage Stochastic Programming (MSSP) framework for incorporating demand uncertainty into the EU-wide RFSC design.

Overarching RQ: What insights emerge when integrating sustainability and uncertainty modeling for renewable fuel supply chain planning, and how can they inform EU-level energy policy?

Overarching RQ integrates the insights gained from sustainability analysis and uncertainty modeling to provide a comprehensive view of RFSC design by combining the findings of the previous RQs. This synthesis also highlights the broader implications for long-term energy planning and policy.

Figure 1-1 provides an overview of the dissertation's structure and illustrates how the RQs are integrated into its two main parts. The Preface outlines the overall aim, methodology, and

key findings and contributions. Chapter 2 reviews the current state of research on RFSCs and positions the dissertation within the context of the identified RQs. Chapter 3 introduces the methodological approaches used to address RQs to design RFSCs with explicit consideration of sustainability and uncertainty. Chapter 4 summarizes the applied methods and highlights the central findings of the research papers. Chapter 5 synthesizes the most important insights, discusses the contributions of the dissertation, and reflects on practical implications, limitations, and future research directions. The cumulative part of the dissertation then presents the three research papers in detail (Chapters 6–8).

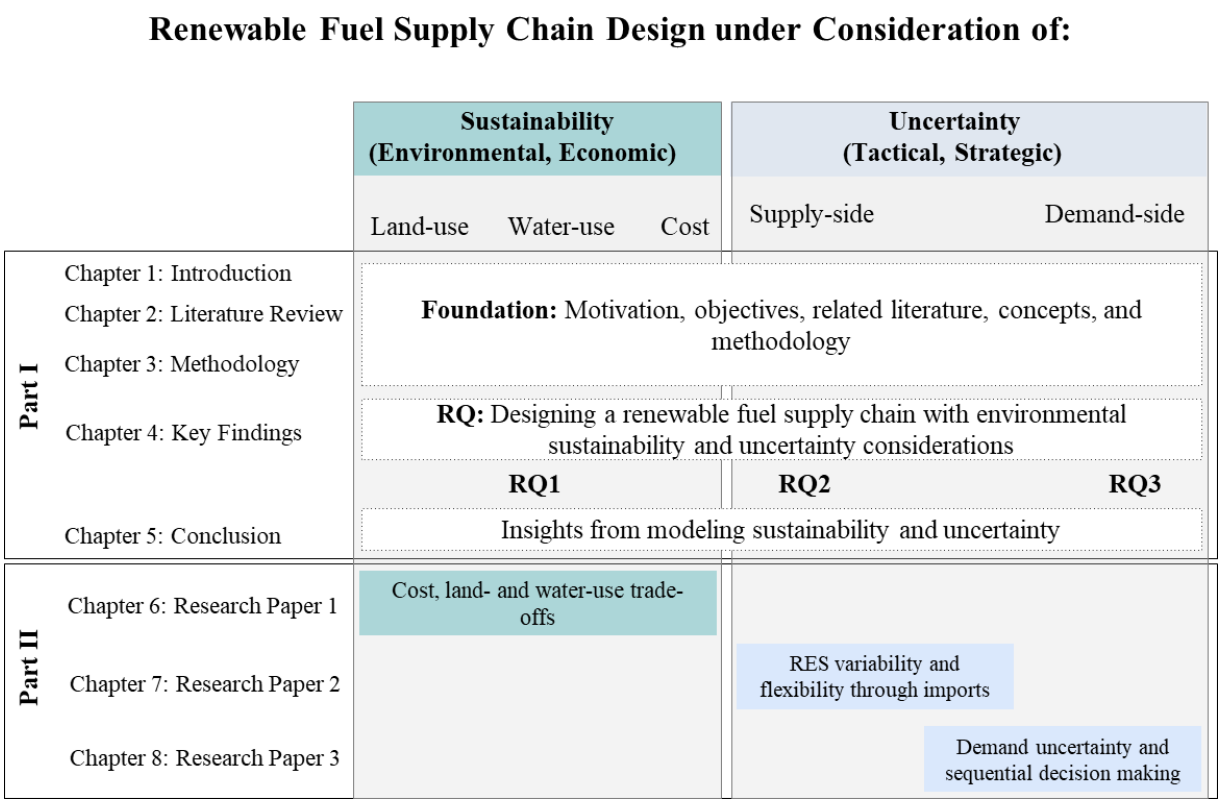


Figure 1-1: Classification of the RQs and associated papers based on their contributions to the two overarching thematic domains, sustainability and uncertainty, and the corresponding organization of the dissertation

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Chapter 2

2 Literature review

Several prior studies address RQs similar to those examined in this dissertation and offer valuable conceptual and methodological foundations. This chapter reviews the current state of the literature on RFSCs and introduces the key concepts and approaches relevant to the RQs, and derives the specific modeling requirements that follow from the literature. The review is organized along the dissertation's two overarching themes (sustainability and uncertainty) and proceeds from the general design problem to the specific dimensions needed to answer the RQs. Section 2.1 provides an overview of RFSC design and related concepts and challenges. Section 2.2 discusses existing research for incorporating environmental sustainability into RFSC planning. Section 2.3 then examines how uncertainty has been addressed in RFSC design. Finally, Section 2.4 consolidates the insights into a research gap and a set of requirements that directly motivate the methodological choices in Chapter 3 and the dissertation's RQs.

2.1 Renewable fuel supply chain design and key challenges

A SC can be understood as a coordinated network of suppliers, production facilities, warehouses, and distribution centers that work together to satisfy customer demand (Matinrad et al., 2013). In such networks, decisions on facility location, production, storage, and transport must be aligned across multiple echelons and time periods. In RFSCs, this general SC design problem becomes substantially more demanding due to the need to replace fossil fuels, dispersed resource bases, emerging conversion technologies, and policy-driven market dynamics. As a result, RFSC modeling frameworks must capture network complexity, multiple fuel/technology pathways and feedstocks, temporal variability across several time scales, and geographically extended, import-dependent supply networks. The following subsections review these core challenge dimensions in a cumulative logic: (i) what makes RFSC design computationally and structurally complex, (ii) why multi-fuel integration is required to reflect realistic decarbonization portfolios, (iii) why models must connect long-term transition decisions with short-term variability, and (iv) why geographic scope and imports are not a detail but a core design feature, particularly for the EU context.

2.1.1 Network complexity and core design challenges

Designing an SC is a complex task that has been widely examined across industries. Mathematical models are commonly used to represent the evolving dynamics and features of SCs. These models differ in structure and scope. Some consider a single period, others span long-term horizons; some address multiple products, while others focus on a single commodity (Melo et al., 2009). Although advanced modeling frameworks can, in principle, capture multi-commodity flows, many applications still analyze one product or resource at a time (De Meyer et al., 2014). The computational complexity of SC network optimization stems from several structural characteristics:

- Facility location and network design decisions (open/close, capacities, assignments) already form an NP-hard combinatorial core (Wike, 1999).
- Adding multiple echelons, products, periods, and modes creates large-scale mixed-integer models with many binary/integer variables and linking constraints (Sadeghi et al., 2023).
- Realistic features, fixed setup costs, economies of scale, inventory decisions, and routing/location-routing couplings, introduce nonlinearity and additional integrality, often leading to MINLP formulations (Dong & Li, 2024; You & Grossmann, 2008).

RFSCs are even more challenging to design because feedstocks, technologies, and markets are highly uncertain, geographically dispersed, and strongly shaped by policy. Key challenges include sustainable feedstock procurement, logistics and storage management, technological and market uncertainty, and compliance with climate and sustainability regulations (Aslani et al., 2024; Reed et al., 2023).

An RFSC typically includes renewable feedstock production, collection, pre-processing, transport, conversion, distribution, and finally blending and delivery to end-use sectors such as road, aviation, marine, and industry. For power-based fuels (e-fuels, green hydrogen derivatives), the chain starts from renewable electricity generation and then includes conversion (electrolysis, synthesis), storage, and transport to demand centers (Gorji, 2023). Major issues include spatial dispersion, weather-driven variability, and competition for resources. In many regions, limited waste and residue availability and tightening sustainability standards lead to “feedstock crunches,” where demand exceeds sustainable supply (Stellingwerf et al., 2022).

Overall, RFSC design must contend with fluctuating resource availability, seasonality, emerging technologies, evolving regulations, and market uncertainty (IRENA & WTO, 2024).

Integrating renewable resources into supply networks brings unique complexities compared with traditional systems due to variable resources, multiple stakeholders, and stringent sustainability requirements. It should address a wide range of issues, balancing economic efficiency, environmental constraints, and logistical challenges. These challenges extend beyond the combinatorial nature of classical facility location and network design. RFSCs typically span multiple echelons and require coordinated decisions across large spatial scales. Yet structural complexity alone does not fully distinguish RFSCs from traditional single-commodity networks. In the context of the energy transition, multiple fuels and conversion pathways must be planned jointly rather than in isolation.

2.1.2 From single-fuel pathways to integrated multi-fuel systems

A defining feature of RFSC planning is that decarbonization of hard-to-electrify sectors is unlikely to be achieved through a single fuel or single pathway. Instead, portfolios of fuels and multiple conversion routes compete for shared resources. Yet, emphasis on single-commodity analyses is common in energy SCs, where research often focuses on individual fuel types or feedstocks rather than integrated systems. In RFSCs, most studies examine resource pathways in isolation, optimizing a single renewable fuel such as a specific biofuel or H2 production and distribution infrastructure (Čuček et al., 2014; Ghaderi et al., 2016; Malladi & Sowlati, 2018; Yue et al., 2014; Zandi Atashbar et al., 2018).

By focusing on a single pathway, many models create rigid systems and miss opportunities to exploit synergies across fuels that could strengthen robustness and reduce costs. While these studies provide important fuel-specific insights, their siloed perspective exposes a key gap. Only a few works incorporate multiple renewable resources or technologies within one flexible network, and only a small number have begun to model integrated multi-fuel or multi-technology configurations (Farajiamiri et al., 2023; Rentizelas et al., 2009; Wolff et al., 2023; Zardoshti Zadeh Yazdi & Walther, 2025).

Even when multiple energy carriers or technologies are discussed together, the analysis often takes a broad energy system perspective rather than a detailed SC network design. For example, high-level scenario studies may include various renewable options without optimizing the specific logistics of each (Albrecht & Nguyen, 2020; Albrecht et al., 2017).

Overall, the limited integration of multiple renewable fuels in SC modeling constrains understanding of how different renewable pathways could be co-developed and coordinated within shared infrastructure to enhance flexibility, robustness, and cost-effectiveness. At the

same time, moving toward more integrated multi-fuel representations not only improves technological realism, but it also highlights a further modeling requirement; RFSC decisions unfold on multiple time scales, such that long-term strategic infrastructure choices must remain compatible with short-term operational variability.

2.1.3 Temporal dynamics: multi-period planning and short-term variability

RFSC decisions are inherently time-dependent because they span different interlinked temporal scales. On the one hand, long-term transition planning determines investment timing, capacity expansion, and technology adoption. On the other hand, short-term operational dynamics govern production scheduling, storage use, logistics, and fluctuations in resource availability. Much of the literature addresses only one of these scales, which can produce designs that are either transition-oriented but operationally infeasible, or operationally detailed but strategically myopic. Therefore, it is vital to represent temporal dynamics in a way that connects long-term structural choices with short-term variability that materially affects feasibility and costs.

Capturing such temporal dynamics is a central challenge in RFSC design. Multi-period optimization frameworks are essential for representing capacity expansion, staged investments, and technology transitions over time, features that single-period models cannot capture (Almansoori & Shah, 2009). In particular, as new technologies such as advanced biorefineries or electrolyzers become cost-competitive, these models determine when and where additional capacities should be deployed.

However, a substantial share of existing research remains static or short-term. Many studies model only a single year or a few periods within a limited region, constraining the generalizability of their findings (Govindan et al., 2017). While such localized models offer detailed case-specific insights, they overlook long-term network evolution and broader policy or demand shifts. In the context of global decarbonization, however, planning horizons must span multiple decades to reflect evolving demand, technology learning, and policy targets, factors that significantly increase model size and complexity. Reflecting this, more studies now employ multi-period frameworks to model investment phasing and system transitions in RFSCs (Hombach et al., 2016; Hombach & Walther, 2015; Lim & Ouyang, 2016; Samsatli & Samsatli, 2018; Wolff et al., 2023).

Short-term temporal variability introduces additional challenges. Renewable resources and demand often fluctuate seasonally or intermittently. Biomass supply is tied to harvesting

cycles, and renewable electricity varies daily and seasonally. To address this, some models use finer time resolutions or seasonal periods and incorporate storage or inventory buffering to smooth supply–demand mismatches (Fattahi & Govindan, 2018; Liu et al., 2017; Quddus et al., 2018; You & Wang, 2011). However, increasing temporal resolution or extending the planning horizon can greatly amplify computational burden, sometimes rendering large-scale models intractable and necessitating decomposition or other advanced solution strategies (Lara et al., 2018; Quarton & Samsatli, 2020).

Balancing model tractability with adequate temporal detail, therefore, remains a key challenge. Nonetheless, capturing both short-term variability and long-term transitions is crucial for representing storage requirements, capacity expansions, demand, and resource availability. Once temporal dynamics are accounted for, spatial scope becomes the next decisive modeling dimension.

2.1.4 Spatial scale, geographic scope, and role of imports

The geographic scope of RFSC models constitutes another key challenge because feedstock availability, potentials, infrastructure siting options, and demand are regionally heterogeneous. Moreover, the literature emphasizes that future renewable fuel markets are likely to be internationally interconnected. Regions with constrained domestic potentials may rely on imports, which introduces strategic trade-offs between domestic production, long-term contracts, and spot-market sourcing. Much of the existing literature focuses on national or sub-national analyses, optimizing SCs within a single country or region. While these localized models offer valuable insights into regional logistics and infrastructure needs, they often overlook interdependencies that arise in an increasingly global energy market.

Decarbonizing fuel supply is a global task, and multi-country SC networks are becoming more relevant as nations plan to trade renewable fuels and feedstocks. Countries with limited biomass or renewable electricity potential may depend on imports of energy carriers, renewable fuels, or resources (Franzmann et al., 2023). This highlights the need for models that optimize not only domestic production and distribution but also cross-border flows and import strategies (Berger et al., 2021). Yet relatively few studies address multi-region or global SCs, and those that do often simplify imports by treating foreign supply as an unlimited resource at a fixed price, without capturing the strategic nuances of imports (Aguirre-García et al., 2025; Haaskjold et al., 2022; Namockel, 2025). In reality, securing a stable supply may involve long-

term contracts, bilateral agreements, or participation in spot markets, each with distinct cost, risk, and flexibility profiles (Görlach et al., 2022; Piria et al., 2022; Wietschel et al., 2021).

These issues are particularly critical for regions with constrained domestic renewable resources (such as the EU), which are expected to import significant quantities of renewable fuels to meet climate targets. Yet current models rarely capture these strategic trade-offs (Vos et al., 2020; Nichol et al., 2023; Shin et al., 2025). There is therefore a clear need for more detailed consideration of international scopes and imports in RFSC models, so that model results are robust and relevant for real-world applications in a global market.

Overall, substantial progress has been made in modeling renewable fuel pathways, network configurations, and temporal–spatial aspects. However, gaps remain in integrated RFSC frameworks that (i) capture network complexity and resource dispersion, (ii) cover multiple fuels, production pathways, and technologies, (iii) link long-term transitions with short-term variability, and (iv) represent multi-regional systems and import strategies. Addressing these gaps is crucial for designing flexible, robust, and cost-effective supply chains for a global low-carbon energy system.

Besides, RFSCs are pursued precisely because of environmental objectives, and the literature increasingly calls for sustainability metrics to be represented explicitly. The next section, therefore, reviews how environmental sustainability is incorporated into RFSC planning.

2.2 Environmental sustainability in renewable fuel supply chain design

The progressive phase-out of fossil fuel production and its associated environmental impacts is a key driver for developing and planning RFSC networks. In this context, environmental sustainability has become a central concern. A systematic review highlights that sustainability, as a major focus of modern SCs, is expanding rapidly (Pourhejazy & Kwon, 2016), yet multi-criteria performance measures are not consistently reflected in optimization-based RFSC design. Existing models differ substantially in their objective functions: most studies employ a single economic objective that either minimizes total cost or maximizes profit (Hombach et al., 2018; Osmani & Zhang, 2013; Walther et al., 2012; Wolff et al., 2023; Zhang et al., 2013), while others extend the formulation by including environmental impacts as additional objectives or as binding constraints (Hombach & Walther, 2015; Nguyen et al., 2019; Samsatli & Samsatli, 2018).

Across the literature, environmental sustainability is operationalized through specific dimensions and indicators that are embedded in RFSC models as (i) additional objective functions, (ii) explicit constraints, or (iii) post-processing evaluation metrics. While climate-related impacts, typically expressed through life-cycle greenhouse gas (GHG) emissions and global warming potential (GWP), dominate the environmental discussion, large-scale deployment pathways also create spatially explicit pressures through land occupation and land use change, as well as resource constraints through freshwater use. These dimensions are particularly relevant when renewable fuel systems shift burdens from emissions to resource use and spatial competition, thereby requiring explicit evaluation of cross-dimensional sustainability.

2.2.1 Environmental dimensions, criteria, and indicators

Environmental assessments in renewable energy systems have been investigated from multiple angles. Across the literature, climate impact, typically measured as life-cycle GHG emissions in CO_2-equivalent and reflected in GWP-related indicators, has become the dominant metric for evaluating environmental performance. Consequently, RFSC models increasingly incorporate GHG-based objectives or constraints to ensure that renewable fuels yield net emissions benefits relative to fossil alternatives (Laborde & Valin, 2012; Nonhebel, 2003; Samsatli et al., 2015; Sitorus & Brito-Parada, 2022). However, renewable fuel systems also generate sustainability pressures that are not fully captured by climate indicators alone, most notably through land-related impacts and freshwater requirements.

2.2.1.1 Land use, land use change, and spatial competition

RFSCs and renewable energy systems can substantially affect land use, yet regional and global decarbonization studies rarely account for the land footprint of energy pathways. Walker (1995) highlighted early concerns regarding land requirements, ecological impacts, and public opposition. Some works explicitly examine cross-sector competition and direct or indirect Land Use Change (LUC) effects (Hombach & Walther, 2015; Laborde & Valin, 2012; Nonhebel, 2003; Osmani & Zhang, 2013; Subramaniam et al., 2019). Others capture land impacts indirectly by constraining or varying land availability for renewable energy sources, often through scenario-based classifications of land types (Cintas et al., 2021; Hoogwijk et al., 2009; MacKay, 2013; Quarton & Samsatli, 2020; Samsatli et al., 2015).

Land sustainability concerns extend beyond agricultural competition (Bernardi et al., 2013). Additional strands address ecological impacts and societal acceptance, including wildlife-oriented wind farm planning (Kati et al., 2021), reclamation strategies for wind and solar

sites (Dhar et al., 2020), and biodiversity conflicts in Germany (Ponitka & Boettner, 2020). These contributions underline that land is not merely an availability constraint, but a multidimensional sustainability criterion that interacts with spatial planning and technology selection.

Although electricity technologies have distinct land requirements, only a limited number of studies provide normalized comparisons, and the overall land implications of renewable energy systems remain contested. Many analyses of 100% renewable energy scenarios nevertheless conclude that additional land requirements are unlikely to constitute a fundamental barrier to the transition (García-Olivares, 2016; Cheng & Hammond, 2017; van de Ven et al., 2021). In parallel, modeling work addresses land competition and land efficiency across scales and sectors, including land-efficient renewable options under competing land uses (Sliz-Szkliniarz, 2013), comparative life-cycle land requirements of conventional and renewable technologies (Fthenakis & Kim, 2009), and ecosystem impacts of bioenergy expansion under increasing land pressure (Guo et al., 2016). At the system level, Trondle (2020) links land requirements and total system costs in future European power systems; at the urban scale, Zhang et al. (2021) relate photovoltaic potential to land use patterns using a deep-learning approach.

Land constraints often appear alongside another critical limiting resource, water, particularly for electrolysis-based pathways, biomass cultivation, and cooling or processing requirements. Therefore, the next section reviews how water use has been incorporated into RFSC and energy-system design.

2.2.1.2 Water use and freshwater constraints

CO_2 emissions represent only one dimension of the environmental impacts associated with supplying energy to a global population of eight billion. Broader environmental pressures, including freshwater consumption, material use, and local impacts, are increasingly recognized as relevant to the feasibility and sustainability of energy transitions. Beyond land, water use is also a critical factor, especially in regions with limited water availability and growing demand pressures (Postel, 2000). Although technically feasible pathways to achieve climate goals have been widely explored, assessments of their implications for water resources remain limited (Jin et al., 2019). Freshwater ecosystems are under increasing pressure, and population growth raises concerns about future water demand. Humanity already appropriates a substantial share of terrestrial evapotranspiration and accessible runoff (Postel et al., 1996), underscoring the urgency of integrating water considerations into energy systems and RFSC design.

From a life-cycle perspective, Jin et al. (2019) compile data on water use across different stages of power generation and analyze differences and uncertainties in water use estimates for various generation technologies. Several studies examine the interaction between water use and biomass for energy, often using the concept of water footprint for different biomass types (Drews et al., 2020; Gerbens-Leenes et al., 2009; Hamilton et al., 2015; Yimam et al., 2015). In parallel, some works investigate water usage in hydrogen production processes (Dincer & Acar, 2014; Lee et al., 2019; Mehmeti et al., 2018; Simoes et al., 2021; Turner, 2004). Further examples include bi-objective greywater footprint minimization for ethanol production (Zhong et al., 2018). Despite these contributions, there remains a lack of research that explicitly assesses water use within RFSC optimization models, indicating an important gap in the integration of water constraints into quantitative planning frameworks.

2.2.2 Approaches for addressing sustainability criteria in renewable fuel supply chains

RFSC studies incorporate sustainability criteria through different modeling choices, most commonly by adding environmental objectives, imposing environmental constraints, or evaluating environmental performance ex post. While many models remain anchored in single-objective economic optimization (Hombach et al., 2018; Osmani & Zhang, 2013; Walther et al., 2012; Wolff et al., 2023), an increasing number of studies integrate environmental indicators, most prominently life-cycle GHG emissions, as either additional objectives or binding constraints (Hombach & Walther, 2015; Nguyen et al., 2019; Samsatli & Samsatli, 2018) . This shift reflects the need to ensure that renewable fuel pathways deliver measurable environmental benefits rather than merely relocating impacts along the supply chain.

Life cycle assessment (LCA) plays a key role in enabling such integration by accounting for emissions across all SC stages, from feedstock production to fuel conversion and end use. Coupling LCA with Mixed-Integer Linear Programming (MILP) optimization allows researchers to quantify and minimize the carbon footprint of alternative RFSC configurations (Samsatli et al., 2015; Sitorus & Brito-Parada, 2022). Examples include LCA-based biofuel supply chain models that jointly assess economic and environmental criteria (Liu et al., 2014; You et al., 2011) and multi-objective formulations in biomass-to-energy networks, showing that incorporating carbon-related objectives can reduce climate impacts with manageable economic trade-offs (Čuček et al., 2012).

To explicitly explore trade-offs between economic and environmental performance, multi-objective optimization has become a prominent modeling approach. Such formulations

enable decision-makers to analyze Pareto-optimal compromises between cost/profit and environmental indicators (e.g., life-cycle GHG emissions, carbon intensity), as demonstrated in multi-objective renewable fuel and bioenergy SC models (Huang et al., 2019; Zardoshti Zadeh Yazdi & Walther, 2025). Methodologically, these models differ primarily in (i) the selection of environmental indicators (climate-only vs. multi-dimensional) and (ii) how objectives are prioritized (objective–objective trade-offs vs. objective–constraint formulations). This distinction matters because it shapes both the interpretability of results (e.g., Pareto frontiers versus compliance solutions) and the types of conclusions that can be drawn for planning and policy.

Beyond climate-related criteria, land and water considerations are addressed through a range of modeling strategies. For land, approaches include explicit land occupation metrics, integration of LUC-related emissions, and indirect representations via land availability constraints or land-type scenarios (Cintas et al., 2021; Garcia & You, 2018; Hoogwijk et al., 2009; MacKay, 2013; Samsatli et al., 2015). For water, sustainability is represented through consumption-based footprints, regional availability limits, withdrawal constraints, or multi-objective formulations that evaluate cost–emissions–water trade-offs (Jin et al., 2019; Zhong et al., 2018). In biofuels, for instance, Bernardi et al. (2013) propose a multi-objective model that maximizes net present value while minimizing carbon and water footprints. Taken together, these approaches illustrate that sustainability-oriented RFSC design increasingly relies on integrated formulations that link economic performance with explicit environmental criteria, while also revealing that land and freshwater constraints are still not consistently embedded in optimization-based RFSC planning.

2.3 Uncertainty in renewable fuel supply chain design

Given that strategic SC decisions (such as facility siting and technology selection) are capital-intensive and largely irreversible, it is crucial to explicitly account for uncertainty to avoid technology lock-in and resource misallocation (Huang et al., 2014; Melo et al., 2009). Accordingly, SC design under uncertainty has received growing attention. However, more empirical research is needed for energy systems and how different uncertainty-handling strategies influence performance (Simangunsong et al., 2012).

2.3.1 Sources of uncertainty in renewable fuel supply chains

RFSCs are subject to a wide range of uncertainties that can be broadly categorized into external uncertainty, network-related uncertainty, and internal uncertainty. External uncertainty refers to the broader context in which RFSCs operate, including environmental, socio-political,

and economic uncertainties. Network-related uncertainty arises from the structure and operation of the supply chain itself and covers supply-side, storage, transportation, and demand-side uncertainties. Internal uncertainty relates to the performance and characteristics of the system elements, such as technology performance, costs (capital and operating), yields, environmental and social impacts, and raw material properties. Against this backdrop, the RFSC literature has focused in particular on the following key uncertainty sources:

- Feedstock supply: Variability in the availability and quality of raw feedstocks (Castillo-Villar et al., 2017; Chen & Fan, 2012; Guo et al., 2022; Huang et al., 2014; Memişoğlu & Üster, 2021; Osmani & Zhang, 2014; Poudel et al., 2018)
- Fuel demand: Fluctuations in demand for renewable fuels due to market dynamics and policy changes (Asadi et al., 2018; Gebreslassie et al., 2012; Gonela et al., 2015; Kalhor et al., 2022; Osmani & Zhang, 2013, 2017; Xie & Huang, 2018; You, 2013)
- Costs and prices: Uncertainty in SC costs (e.g., feedstock costs, processing costs) and fuel selling prices, often influenced by policy incentives and commodity markets (Awudu & Zhang, 2013; Cobuloglu & Büyüktahtakın, 2017; Gonela et al., 2015; Kim et al., 2011; Osmani & Zhang, 2014; Zhang & Osmani, 2015).
- Disruption risks: The possibility of disruptions such as facility outages or transportation link failures, which are sometimes modeled via probabilities of failure in the network (Gebreslassie et al., 2012; Marufuzzaman et al., 2014; Marufuzzaman & Ekşioğlu, 2017; Poudel et al., 2016; Tang, 2006).

Despite extensive work on feedstock and other uncertainties, renewable electricity supply variability remains underexplored. Many SC models treat electricity availability as a fixed exogenous input (Lara et al., 2018), ignoring the intermittency of wind and solar resources (Kwon, 2010; Quan et al., 2015; Zhang et al., 2020), even though it strongly affects production scheduling, storage needs, and overall SC design (Dell'Aversano et al., 2024). One notable exception is the work of Osmani & Zhang (2014) which explicitly incorporates wind power variability into an RFSC model.

Overall, despite growing recognition of these uncertainty drivers, advanced modeling and optimization approaches tailored to RFSCs remain limited. In particular, there is still insufficient understanding of how both (i) renewable resource variability (e.g., wind and solar availability) and (ii) long-term demand uncertainty influence RFSC investment timing, capacity choices, operational policies, and the resulting system configuration over time.

2.3.2 Approaches for addressing uncertainty in renewable fuel supply chains

A variety of approaches have been used to address uncertainty in SC design, including stochastic programming (SP) for recourse-based and risk-averse models that incorporate uncertainty within a probabilistic framework (Santoso et al., 2005), robust optimization formulations that hedge against worst-case scenarios (Pishvaee et al., 2011), fuzzy/possibilistic programming to represent imprecise data as fuzzy numbers or possibility distributions (Ji et al., 2007), scenario-based planning to capture discrete future outcomes (Azaron et al., 2020). Many of these methods were initially developed for general SC contexts and are only gradually being adapted for renewable fuels.

Decision-making environments under uncertainty can be grouped into three categories (Govindan et al., 2017), depending on the level of available information about the input data (Pishvaee et al., 2020): randomness, epistemic, and deep uncertainty.

1. Epistemic uncertainty stems from limited knowledge and low data credibility, often represented via linguistic terms or expert judgment. It is typically modeled with possibilistic and fuzzy programming to capture ambiguity in preferences and assessments (Babazadeh et al., 2017; Ebadi Torkayesh et al., 2024; Fallah et al., 2015; Hendiani & Walther, 2023; Mousazadeh et al., 2015; Tong et al., 2014).
2. Deep uncertainty arises when no reliable objective or subjective probability distributions can be specified and only parameter bounds are known. In this setting, robust optimization seeks solutions that perform well under worst-case realizations, often via interval-based formulations for continuous parameters or scenario-based robust models for discrete ones (Bairamzadeh et al., 2018; Delkhosh & Sadjadi, 2020; Ghelichi et al., 2018; Hombach et al., 2018; Kalhor et al., 2022; Tay et al., 2013).
3. Randomness assumes sufficient, reliable historical data to estimate probability distributions and to check that past patterns remain plausible. Here, SP, including chance-constrained programming, TSSP, and MSSP, can be applied; if data adequately represent the uncertainty domain, SP can deliver robust, high-quality solutions (Aboytes-Ojeda et al., 2019; Li et al., 2022; Memişoğlu & Üster, 2021; O'Neill et al., 2022; Zarei et al., 2022).

SP is particularly attractive because it explicitly balances decisions, economic performance, and system resilience, albeit at the cost of higher data and computational requirements. In RFSCs, TSSP has been widely applied, especially in biofuel and hydrogen SCs, to address uncertainties in biomass and feedstock supply, conversion yields, demand, logistics, and infra-

structure design (Aboytes-Ojeda et al., 2022; Almansoori & Shah, 2009, 2012; Chen & Fan, 2012; Dal-Mas et al., 2011; Dayhim et al., 2014; Gonela et al., 2015; Li & Hu, 2014; Nunes et al., 2015; Osmani & Zhang, 2013; Reuß et al., 2017). Multi-period extensions capture seasonality and time-varying supply (Huang et al., 2014; Poudel et al., 2016; Quddus et al., 2017, 2018), and recent work combines TSSP with data-driven robust optimization and multi-uncertainty formulations (Efthymiadou et al., 2025; Zhou et al., 2024). Overall, these contributions show that explicitly modeling uncertainty improves the cost-effectiveness and resilience of RFSCs, yet much of the literature still relies on simplified uncertainty representations, often considering a limited set of uncertain drivers, coarse temporal resolution, or small scenario sets, thereby restricting insights into how uncertainty jointly affects long-term design and operational recourse (Govindan et al., 2017).

For long-term strategic planning, TSSP representation is restrictive because it cannot capture how information is gradually revealed, and decisions must adapt over time. MSSP explicitly models sequential decision-making under uncertainty (Birge & Louveaux, 2011). Usually, uncertain parameters are represented by scenario trees calibrated from historical data or forecasts, allowing capacities, resource allocations, and operations to be updated at multiple stages as new information becomes available (Fattahi et al., 2017, 2018; Fattahi & Govindan, 2018; Nickel et al., 2012; Xie & Huang, 2018). Despite its suitability for multi-decade investment pathways and adaptive system expansion, MSSP remains underexplored in RFSC design, leaving a gap for planning diversified, flexible networks under uncertainty. Chapter 3.3 details how this dissertation applies TSSP and MSSP to RES and demand uncertainty in RFSC design.

Table 2-1: Overview of selected studies

Study	Multiple resources	Multiple storage	Multiple transportation	Seasonality	Multi Period	Uncertainty method	Uncertain parameter	Case study
(Efthymiadou et al., 2025)	✓			✓	✓	TSSP	Demand, Biomass availability, Gas price, Technology costs	UK
(Kim et al., 2024)				✓		TSSP	RES, Demand	9 Regions
(O'Neill et al., 2022)				✓	✓	TSSP	Biomass yield	Michigan
(Guo et al., 2022)				✓	✓	TSSP	Biomass supply	Illinois
(Aboytes-Ojeda et al., 2022)				✓		TSSP	Biomass quality, Biomass yield	Texas
(Memişoğlu & Üster, 2021)				✓	✓	TSSP	Biomass yield	Texas
(Nur et al., 2021)			✓	✓	✓	TSSP	Biomass quality	South central US
(Aboytes-Ojeda et al., 2019)				✓		TSSP	Biomass supply	Texas

(Sharma et al., 2019)				✓		TSSP	Biomass yield	Tennessee
(Ghelichi et al., 2018)	✓			✓	✓	TSSP	Feedstock supply, Demand	Iran
(Osmani & Zhang, 2017)	✓		✓	✓	✓	TSSP	Biomass supply, Demand, Selling price	Wisconsin
(Castillo-villar et al., 2017)						TSSP	Biomass quality	Tennessee.
(Nunes et al., 2015)				✓	✓	TSSP	Demand	UK
(Zhang & Osmani, 2015)			✓	✓		TSSP	Biomass supply, Demand, Sale price	Alabama
(Dayhim et al., 2014)	✓				✓	TSSP	Demand	New Jersey
(Osmani & Zhang, 2014)	✓		✓	✓	✓	TSSP	Biomass supply, Purchase price of biomass, Demand, Sale price of bioethanol	4-state mid-western region in the US
(Marufuzzaman et al., 2014)			✓			TSSP	Biomass supply, Technology	Mississippi.
(Huang et al., 2014)			✓	✓	✓	TSSP	Feedstock supply	California
(Azadeh et al., 2014)					✓	TSSP	Demand, Price	Iran
(Osmani & Zhang, 2013)	✓		✓	✓		TSSP	Biomass supply, Purchase price of biomass, Demand, Sale price of bioethanol	North Dakota
(Awudu & Zhang, 2013)						TSSP	Demand, Price	North Dakota
(You, 2013)			✓		✓	TSSP	Supply, Demand	Illinois.
(Almansoori & Shah, 2012)	✓	✓		✓	✓	TSSP	Demand	UK
(Gebreslassie et al., 2012)					✓	TSSP	Supply, Demand	Illinois
(Chen & Fan, 2012)			✓	✓		TSSP	Feedstock	California
(Kim et al., 2011)			✓			TSSP	Supply amounts, Market demands, Market prices, Processing technologies	Southeastern region of the US
(Kim et al., 2008)		✓	✓			TSSP	Demand	Korea
(Mitrai et al. 2026)			✓	✓	✓	MSSP	Market price	California
(Shuai et al. 2024)	✓				✓	MSSP	Demand	Asia
(Zarei et al., 2022)	✓	✓	✓	✓	✓	MSSP	Biomass supply, Demand	South Korean
(Fattahi & Govindan, 2018)			✓	✓	✓	MSSP	Biomass supply, Disruption occurrence at each storage facility	Iran
(Xie & Huang, 2018)		✓	✓	✓	✓	MSSP	Biomass supply	South Carolina

2.4 Research gap

This literature review shows that substantial progress has been made along each individual dimension of RFSC planning, network design, sustainability integration, and uncertainty modeling. At the same time, notable gaps remain in how RFSCs are represented, particularly when multiple fuels/resources, environmental constraints, and long-term uncertainties must be addressed, and these streams remain only partially connected.

First, there is a structural and system-level gap in RFSC modeling. Many studies focus on single products or limited pathway combinations and are restricted to national or sub-national scales. While useful for regional logistics, they overlook interdependencies in a globalizing renewable fuel market. Only a few works consider multi-country or multi-region networks, and those that do often model imports in a highly simplified way, for instance by treating foreign supply as an unlimited resource at fixed prices. Imports are usually represented as a single aggregated flow without distinguishing between long-term contracted volumes and flexible spot purchases, so their specific effects on system costs, supply security, and flexibility remain largely unexplored, despite their likely importance for resource-constrained regions such as the EU. Overall, existing contributions rarely provide integrated frameworks that capture network complexity, diverse fuels, resources, and technologies, temporal variability, and geographically extended, import-dependent supply networks.

Second, important environmental sustainability gaps persist. Early RFSC models largely emphasize single-objective cost minimization and thus overlook broader environmental externalities beyond GHG emissions. More recent studies begin to integrate climate indicators into bi- or tri-objective formulations, yet multi-criteria performance measures remain underrepresented, particularly when it comes to land and water use. To the best of the author's knowledge, there is a lack of studies that explicitly quantify the land area required by the overall RFSC and endogenously optimize land use within system design, and assessments of water implications in energy transitions remain limited. Although several works quantify water use for power generation or biomass production, there is still a shortage of RFSC optimization models that treat water use as a decision-relevant constraint or objective. This highlights an important gap in integrating land and water constraints into quantitative planning frameworks for RFSCs.

Third, there is a pressing need to systematically consider uncertainty and the inherent variability of key parameters and data in RFSC analysis. Existing studies recognize multiple uncertainty sources, such as feedstock supply, fuel demand, costs and prices, and disruption risks, but a comprehensive understanding on how these uncertainties influence overall system performance in RFSC remains limited. Tactical uncertainties in parameters and data, such as short- to mid-term fluctuations in RES generation, are often simplified or ignored. In particular, many RFSC models still rely on deterministic averages for renewable electricity availability, treating power supply as an exogenous, fixed input. Integrating these fluctuations into renewable fuel production and SC models remains underexplored, leaving limited insight into how

renewable resource variability and other operational uncertainties propagate through emerging RFSCs and shape investment and operational strategies.

Furthermore, strategic uncertainty is not yet fully captured in RFSC design. Long-term uncertainties, such as the evolution of fuel demand, technology deployment, and policy frameworks, require planning approaches that can account for how information is gradually revealed and how investment and operational decisions must adapt over time. While MSSP is conceptually well-suited to represent such sequential decision-making under uncertainty, its application to RFSCs remains limited. In particular, there is still a lack of MSSP-based RFSC models that endogenously address long-term demand uncertainty and support the design of diversified, flexible supply networks under deep uncertainty.

Altogether, the literature reveals a combined gap. Few studies develop RFSC models that (i) represent integrated, multi-fuel and multi-region networks, (ii) incorporate land use and water use alongside economic objectives, (iii) explicitly model renewable electricity variability, import strategies, and (iv) apply multi-stage stochastic planning to long-term demand uncertainty within a unified framework.

These gaps motivate the dissertation's research questions and methodological choices. Specifically, the dissertation develops a unified RFSC design framework that (i) represents integrated, multi-fuel, multi-region networks; (ii) evaluates trade-offs between economic performance, land use, and water use; (iii) captures renewable electricity variability and import strategies; and (iv) supports adaptive planning along uncertain demand trajectories. The subsequent chapters build on these insights. The research questions formulated in Chapter 1 and the methodological approaches presented in Chapter 3 are designed to respond directly to these gaps, and the three research papers (Chapters 6–8) collectively provide evidence on how large-scale RFSCs can be planned under sustainability and uncertainty considerations.

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Chapter 3

3 Research methods

This chapter presents the methodological foundations used throughout the dissertation to model and solve RFSC network design problems under sustainability and uncertainty considerations. The underlying decision problem is formulated as a strategic–tactical optimization model to design the RFSC and analyse the associated decisions (Section 3.1). Building on this backbone, the environmental sustainability of the RFSC is assessed through a multi-objective optimization framework that enables the systematic representation and exploration of trade-offs between economic and environmental objectives (Section 3.2). Subsequently, scenario-based stochastic programming approaches to represent and address tactical and strategic uncertainty on both the supply and demand sides are presented (Section 3.3). The following subsections summarize the purpose and methodological rationale of each applied approach.

3.1 Modeling framework and strategic-tactical optimization

Designing RFSCs calls for mathematical programming approaches that can capture network-scale interdependencies, multi-period system evolution, and the tight coupling of production, storage, transportation, and resource use. Mixed-integer linear programming (MILP) is widely used for such settings because it supports large-scale planning under diverse techno-economic scenarios while preserving a transparent representation of system constraints and trade-offs (Kallrath, 2000).

3.1.1 Network-based MILP for renewable fuel supply chain design

RFSC planning inherently links decisions made at different time scales. Strategic decisions, such as facility-siting, technology selection, capacity expansion, and transport infrastructure, shape the long-term system layout, while tactical decisions, such as production levels, storage operation, routing, and procurement, govern operational feasibility and performance. MILP accommodates this structure by combining discrete investment decisions with continuous flow variables that enforce material and energy balances through linear techno-economic relationships.

Building on these capabilities, this dissertation develops a strategic–tactical optimization model that determines the cost-effective configuration of RFSCs, including the type, number, location, and utilization of production and storage facilities, transport modes, and resource procurement options. The model identifies designs that satisfy regional supply–demand requirements and operational constraints while minimizing total system cost and, where relevant, additional performance indicators such as land and water use. This provides a consistent basis for comparing renewable fuel pathways and assessing their ability to meet techno-economic and environmental objectives across varying energy-system conditions and under uncertainty

To flexibly represent the relationships between resources, technologies, and flows, the model adopts the Resource–Technology–Network (RTN) approach (Samsatli et al., 2015). In RTN models, conversion technologies and resources are represented as different nodes that transform input resources into intermediate products and final fuels, while the network structure represents spatially distributed flows, storage, and transport. RTN supports multi-commodity modeling and is particularly useful for RFSCs where multiple fuels and intermediates share infrastructure and compete for common resources.

3.1.2 Time structure: strategic and tactical decisions

RFSC design is inherently time-dependent. To reflect long planning horizons while also representing seasonal dynamics, the model adopts a time-decomposition structure that distinguishes between strategic and tactical decisions. This hierarchical time aggregation improves tractability while retaining the essential coupling between long-term infrastructure choices and short-term feasibility and cost drivers. Accordingly, the number and length of strategic periods and the selection of representative intra-period slices are modeling parameters that should be aligned with the decision context and data availability.

Within this decision-making framework, strategic decisions are defined on coarse time steps (e.g., decadal) and determine the long-term supply chain configuration, including technology choices, facility siting and sizing, capacity expansion, major capital investments, and import contracting. Tactical decisions are defined on a finer time scale (e.g., seasonal) within each strategic period and govern production levels, storage operations, transportation flows, spot imports, and feedstock procurement. This two-level structure follows established time-aggregation approaches for long-term planning (Samsatli et al., 2015) and helps manage the large number of decision variables typically associated with multi-period, high-resolution planning models (Lara et al., 2018; Quarton & Samsatli, 2020). By linking long-term capacity in-

vestments with flexible operational decisions, the hierarchical structure provides a versatile modeling backbone that can be adapted to different RFSC design research questions; in general, the strategic period length and the number of seasonal subdivisions remain adjustable parameters depending on the application.

3.1.3 Import mechanisms and sourcing flexibility

In line with the discussion in Chapter 1 on structural import dependence and strategies, the model explicitly distinguishes two import mechanisms for each fuel, namely contracted imports and spot imports. Contracted imports, representing long-term agreements or reserved capacities that are decided strategically and provide a predictable supply at negotiated cost. Spot imports, representing flexible purchases, are used to cover residual demand when domestic supply, storage, and contracted imports are insufficient, typically at a higher unit cost. Separating these mechanisms provides a parsimonious way to represent the commitment–flexibility trade-off in sourcing and prevents imports from being treated as an unrealistically frictionless balancing option.

3.2 Environmental sustainability and multi-objective optimization

Sustainability-aware RFSC planning often requires evaluating designs against multiple, potentially conflicting criteria. Multi-objective optimization provides a systematic framework to quantify such trade-offs and to derive decision alternatives that make tensions and synergies transparent.

3.2.1 Multi-objective problem definition

Within the broader sustainability context, multi-objective solution techniques such as the ε-constraint method, weighted-sum approaches, and evolutionary algorithms are widely applied in this field (Nonhebel, 2003; Sitorus & Brito-Parada, 2022). These methods generate sets of non-dominated solutions that make the tensions and synergies between economic and environmental objectives explicit. To handle the technological and regional heterogeneity of renewable fuel systems, transparency regarding methods, trade-offs, and system designs must be supported by advanced decision-making tools (Ramos et al., 2022).

A generic multi-objective optimization problem can be written as:

$$\min \ \big(f_1(x), f_2(x), \dots, f_k(x)\big) \qquad \text{s.t.} \quad x \in \mathcal{X}$$

Where $x$denotes the vector of decision variables and $\mathcal{X}$ is the feasible region defined by the MILP constraints. A feasible solution is Pareto-efficient (non-dominated) if no other feasible solution improves one objective without worsening at least one other objective (Liu et al., 2020). The set of Pareto-efficient solutions (the Pareto frontier) characterizes the achievable trade-off surface and provides decision support when no single objective can be optimized in isolation.

3.2.1.1 Economic objective function

Economic performance is commonly captured by total system cost over the planning horizon. When long-lived investments and multi-period operation are present, costs are frequently expressed as a net present value (NPV) of capital investments, fixed operating and maintenance costs, and variable costs. By discounting future expenditures, NPV-based formulations enable consistent comparison of designs with different investment timing and operational profiles.

In this dissertation, the economic viability of the RFSC is assessed through the NPV of total system cost. The formulation reflects the underlying cost structure by distinguishing between strategic and tactical cost components, each of which may comprise fixed and variable terms. Fixed costs are evaluated for representative periods and include cost parameters that vary across SC components, derived from techno-economic data for the respective technologies and facilities. Variable costs are determined by prices of resources and services, such as transportation, where they accrue per unit distance and reflect the associated resource consumption.

3.2.1.2 Environmental objective function

Environmental sustainability can be represented through explicit objective functions (or constraints) that quantify key resource footprints, with land use and water use as two important indicators for RFSC.

Land use is quantified for renewable electricity generation using surface power density, which relates energy generation to required area, and for energy crops using crop yields (e.g., tons per hectare) together with feedstock requirements implied by production volumes. In this work, land use for renewable electricity generation is calculated using surface power density (Smil, 2010), defined as the rate of energy flow per unit surface area [W/m²], while land use for energy crops is determined from crop yields (Fischer, 2015).

Water impacts are quantified using the water footprint (Hoekstra & Chapagain, 2006; Hoekstra & Hung, 2002), defined as the annual volume of freshwater used to produce goods and services, and applied here to calculate the water used for energy crops and the water con-

sumed in H_2 production. When included as objectives, these indicators enable explicit analysis of economic–environmental trade-offs; when included as constraints, they enforce sustainability limits.

Building on this, the model requirements in this work are derived from the potential environmental impacts of the RFSC network. In particular, environmental limits on land and water, strongly shaped by geography and topography, must be captured to support a net-zero transition by 2050. Against this backdrop, jointly minimizing land use, water use, and total system cost becomes essential, both for designing climate-neutral RFSCs and for clearly communicating the trade-offs inherent in alternative SC configurations.

3.2.2 Solution method

A Pareto-based approach is adopted to elucidate trade-offs between conflicting objectives. Several techniques exist to compute or approximate Pareto frontiers (e.g., weighted sums, evolutionary algorithms, ε-constraint methods). For MILP-based network design problems, the ε-constraint method is particularly attractive because it optimizes one objective directly, converts the remaining objectives into constraints with bounds (ε-levels), and solves a series of single-objective MILPs while varying ε-levels to trace the Pareto frontier. This approach is particularly suitable due to its conceptual simplicity, explicit treatment of constraints, transparent exploration of trade-offs, well-understood solution space, and computational efficiency (Zhang & Reimann, 2014).

However, a known limitation of the classical ε-constraint approach is that it may produce weakly efficient or redundant solutions under certain settings and does not always guarantee Pareto-efficient solutions, especially when more than two objectives are considered (Khorram et al., 2014). This limitation is addressed by the augmented ε-constraint (AUGMECON) method, which introduces non-negative slack variables and transforms the inequality-constrained objectives of the conventional ε-constraint formulation into equality constraints, thereby ensuring that all solutions obtained are Pareto-efficient (Mavrotas, 2009; Mavrotas & Florios, 2013). This enhanced variant enables a thorough exploration of the solution space, captures diverse trade-offs and preferences, and performs well in complex optimization problems with multiple objectives and constraints, thereby providing decision support to policymakers and investors and increasing transparency in the presence of conflicting objectives.

In this dissertation, a multi-period, multi-objective MILP is solved using AUGMECON implemented in Python/Gurobi to construct an efficient Pareto frontier and to capture diverse trade-offs and preferences for policymakers and investors.

3.3 Optimization under uncertainty

Deterministic planning can produce designs that are cost-optimal under nominal assumptions but suboptimal or infeasible when key inputs deviate from forecasts. SP provides a structured way to incorporate uncertainty by representing uncertain parameters through scenarios with associated probabilities and optimizing decisions with respect to expected performance. SP is particularly attractive because it balances economic performance and system resilience, despite higher data and computational requirements (Birge & Louveaux, 2011).

Section 2.3 reviewed different methodological approaches for handling uncertainty in RFSCs and highlighted the prominent roles of TSSP and MSSP in the literature. In this dissertation, these two formulations are applied in a complementary way. RES variability is treated as a tactical uncertainty and modeled using a TSSP framework, while long-term fuel demand is treated as a strategic, time-dependent uncertainty and represented via an MSSP framework. Building on the strategic–tactical MILP framework introduced in Sections 3.1, TSSP and MSSP are used to link long-term infrastructure investments with tactical decisions under uncertainty. The following subsections summarize the specific methodologies used in this dissertation.

3.3.1 Two-stage stochastic programming

A two-stage stochastic MILP framework can be used to support the design of RFSC under uncertain RES. The approach separates long-term, irreversible planning decisions from short-term, adaptive operating decisions. In the first stage (“here-and-now”), strategic variables are fixed before uncertainty is realized and therefore apply uniformly across all scenarios. Typical first-stage decisions include the selection of technologies, the siting and sizing of facilities, the sizing of transport and storage infrastructure, and the choice of procurement instruments such as long-term import contracts.

In the second stage (“wait-and-see”), recourse decisions are adjusted after the uncertain parameters become known and can be updated for each tactical period and scenario. These operational variables govern how the system is run given the realized conditions, including resource allocation, production quantities, inventory and storage operation, transportation flows, and short-term procurement. This structure links investment planning with scenario-de-

pendent operations, allowing the system to respond to fluctuations in renewable electricity availability while accounting for the cost implications of that flexibility. The resulting model, therefore, evaluates designs based on expected performance across scenarios, typically through minimization of expected total system cost, while capturing the value of adaptive operations under uncertainty (Birge & Louveaux, 2011). In this way, TSSP links irreversible infrastructure investments with adaptive operations, ensuring robust and cost-efficient SC designs under uncertainty, while minimizing expected system costs and maintaining flexibility and robustness to RES fluctuations.

The objective typically optimizes expected value across scenarios:

$$\min_{x} \; c^{\top}x + \mathbb{E}_{\omega}[Q(x,\omega)]$$

Where $x$are first-stage decisions and $Q(x,\omega)$is the optimal second-stage cost in scenario ω. TSSP is especially useful when uncertainty affects operational feasibility and costs, but strategic decisions must be made upfront.

Weather drives wind/solar availability, so the renewable electricity supply fluctuates (Staffell & Pfenninger, 2016). Using 30 years of capacity-factor data, RES uncertainty is represented through scenarios. For each country and season, the mean and variance are estimated for solar, onshore wind, and offshore wind, a normal distribution is fitted, and the fit is validated using a Kolmogorov–Smirnov test. The resulting distributions are discretized via the percent point function at the 33rd, 66th, and 99th percentiles to define low/medium/high states, capturing both typical and extreme conditions with limited complexity. In total, 244 uncertain parameters are considered (solar and onshore wind: 26 countries × 4 seasons; offshore wind: 9 countries × 4 seasons), each with three scenarios. Scenarios form a four-period tree with three branches per period ($3^4 = 81$ pathways per country–RES); pathway probabilities are the products of branch probabilities and sum to one. The tree is embedded in the decision model; all scenario values are reported in the supplementary material.

3.3.2 Multi-stage stochastic programming

A MSSP framework provides a structured way to design supply chains when demand evolves over time and is revealed sequentially. Unlike two-stage models, MSSP represents uncertainty as a staged information process and links long-term investment decisions with operational planning across multiple periods. This enables adaptive planning, decisions can be re-

vised as new demand information becomes available, while still respecting the limited foresight available at each point in time.

A common implementation begins with scenario generation for the uncertain demand process. When demand exhibits temporal dependence, scenarios can be produced from a time-series model such as an autoregressive process. Because multistage formulations can become computationally large, scenario reduction is typically applied to retain a representative but tractable scenario tree; forward selection heuristics are one established option for selecting a subset of scenarios that preserves key distributional features while reducing complexity.

In the decision structure, capital-intensive infrastructure variables (e.g., facility siting, capacity expansion, and technology selection) are modeled as largely irreversible and therefore particularly sensitive to long-horizon demand uncertainty. Treating demand deterministically can bias designs toward either overinvestment (excess capacity and stranded assets) or underinvestment (insufficient capacity, reliance on expensive short-term procurement, or unmet demand). MSSP addresses these risks by explicitly modeling sequential decision-making: initial strategic decisions are taken before uncertainty is revealed, and in each subsequent period additional investment and operational decisions are chosen as recourse actions conditional on the information observed up to that stage.

A central requirement is non-anticipativity. It enforces that decisions at a given stage must be identical across scenarios that share the same information set, ensuring that the model does not exploit knowledge of future realizations and that solutions are implementable and time-consistent. MSSP can be formulated as a nested sequence of two-stage stochastic programs with implicit non-anticipativity, or as a single extensive-form model with explicit non-anticipativity constraints (Dupačová, 1995). The latter provides direct control over information structure and scenario coupling and is widely used in practical implementations.

Following prior work (Dilaver & Hunt, 2021; Zimberg et al., 2019), fuel demand is modeled as a temporally dependent stochastic process. Time-dependent demand scenarios are generated with a modified first-order autoregressive model (Fattahi et al., 2017, 2018; Fattahi & Govindan, 2017; Sodhi, 2005). Because scenario generation can create too many realizations, scenarios are reduced to a computationally manageable subset that still approximates the underlying distributions (Heitsch & Römisch, 2005). Monge–Kantorovich distance–based was applied for scenario reduction (Dupacova et al., 2003; Heitsch & Römisch, 2003, 2009; Rachev

& Rüschendorf, 1998) using a forward selection heuristic (Römisch & Wets, 2007), yielding a reduced scenario fan that preserves key statistical properties while remaining tractable.

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Chapter 4

4 Key findings

This chapter summarizes the key findings of the dissertation and three research papers. All research papers provide decision support tools for designing RFSCs, applying an optimization model, which is adjusted to the requirements of each analysis. Quantitative results from the three case studies are reported subsequently as illustrations of the general mechanisms and implications revealed by the framework. All three research papers build on a shared RFSC modeling backbone that represents multiple renewable resources, conversion routes, spatial infrastructure decisions, and multi-period planning. The shared structure ensures comparability across studies while allowing each analysis to focus on a specific research question and uncertainty/sustainability dimension.

The case study models a renewable-fuel supply chain with multiple renewable resources, intermediate carriers, and final products. Seasonal feedstock variability is represented, and multiple production pathways and technology options (with discrete capacity levels and learning-driven cost reductions) are available throughout the horizon. The network includes transport and storage options, and multiple regions with heterogeneous resource potentials and demand. Two import strategies are considered: long-term contracted imports and spot imports used only to cover shortfalls. The EU+UK application spans 2021–2060, split into four decadal strategic periods with seasonal subperiods for tactical operation.

Analyses are grouped into environmental sustainability considerations (Research Paper 1) and uncertainty considerations (Research Papers 2 and 3). A shared overarching database enables comparison across the three studies, although each paper applies updated and refined input data. While Research Papers 1-3 mainly address RQ1–RQ3, their combined findings are synthesized to answer the overarching RQ, which focuses on overall design implications and policy-relevant lessons for RFSC development.

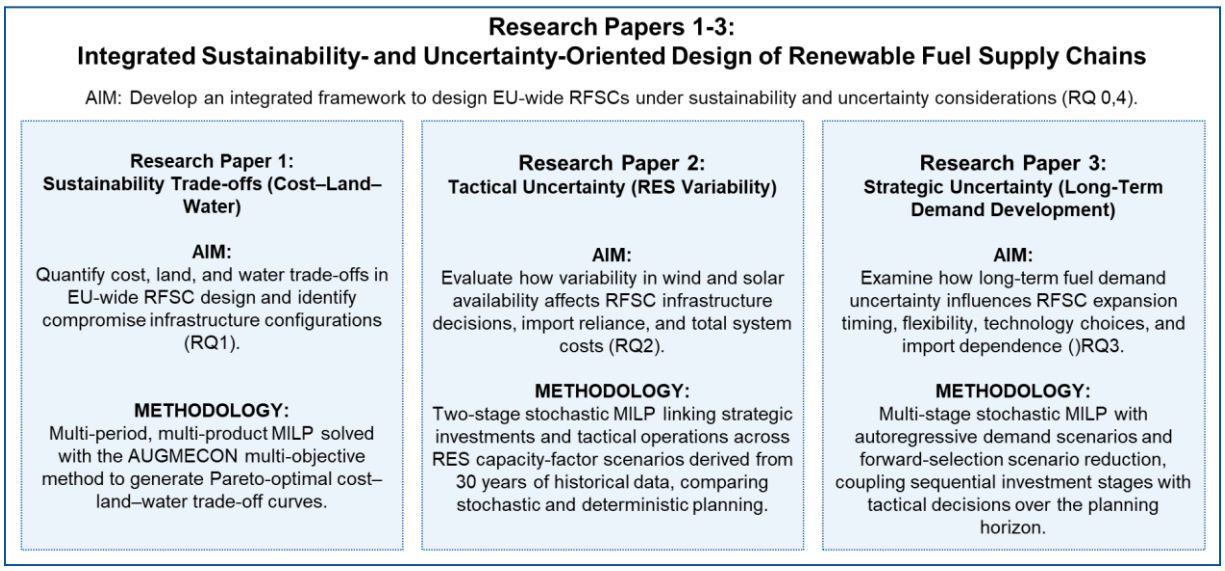


Figure 4-1: Overall dissertation approach, outlining the aims and methodological frameworks of the three research papers

4.1 Integrated findings across the dissertation

This section provides an integrated synthesis of the dissertation's contributions, linking the gaps identified in the literature to the modeling requirements and methodological choices that guide the subsequent analyses.

The literature review indicates substantial progress in modeling individual aspects of RFSCs, yet it also reveals that these streams remain only partially integrated. A first gap is structural and system-level: many RFSC studies focus on single products or limited pathway combinations and remain restricted to national or sub-national scales, thereby missing system interactions in increasingly international markets. In particular, imports are often represented in a simplified manner (e.g., as an unlimited external supply at fixed prices) and typically not differentiated by contracting logic, leaving the role of long-term commitments versus flexible purchases underexplored. A second gap concerns environmental sustainability operationalization. While recent work increasingly incorporates climate indicators, multi-criteria sustainability representations remain limited, especially for land use and water use, despite their relevance for large-scale deployment and competition for scarce resources. A third gap relates to long-term planning under uncertainty. Even when models include realistic network structures and sustainability metrics, planning recommendations can be fragile if variability in renewable electricity availability or long-term demand evolution is not represented with decision structures that separate long-term commitments from adaptive actions.

From these gaps, the dissertation derives the following modeling requirements for transition-relevant RFSC decision support. Integrated multi-fuel, multi-resource network representation. The model must represent multiple fuels, resources, and conversion routes simultaneously to capture competition for shared inputs and infrastructure interactions. Multi-period planning with a strategic–tactical time structure. The framework must link long-lived investment decisions to intra-period operational feasibility, including seasonal variability where it materially affects costs and feasibility. Explicit sustainability criteria beyond cost. Sustainability must be represented through explicit indicators that allow trade-off analysis, with particular emphasis on land and water alongside economic performance. Endogenous import and sourcing strategies with commitment vs flexibility. Imports must be modelled in a way that distinguishes strategic long-term sourcing commitments from flexible short-term balancing options, enabling evaluation of security/flexibility implications. Decision-making under uncertainty with non-anticipative structure. The framework must represent uncertainty in a way that separates here-and-now commitments from recourse actions and allows adaptation as information becomes available over time. These requirements define the dissertation's contribution beyond any single case study: they specify what an RFSC model must represent to address the research questions in a scientifically defensible way.

A further dissertation-level finding concerns method selection: each requirement implies a class of modeling and solution approaches that is appropriate for the problem structure. Multi-objective optimization to reveal sustainability trade-offs. Because cost, land use, and water use can be conflicting objectives, a single-objective formulation is insufficient for sustainability-aware planning. Multi-objective MILP approaches are therefore required to generate Pareto-efficient alternatives and to identify compromise configurations in a transparent manner. Two-stage stochastic programming for renewable electricity variability. Variability in renewable electricity affects operational feasibility and costs, yet infrastructure decisions must be made in advance. A two-stage structure is therefore appropriate to separate long-term investment commitments from short-term recourse decisions under realized renewable availability. Multi-stage stochastic programming for long-term demand evolution and adaptive planning. Demand uncertainty unfolds over decades and requires sequential adaptation of decisions. A multi-stage structure is therefore suitable to represent evolving information and to quantify the value of flexibility relative to static planning.

Against this dissertation-level foundation, the following sections report the findings of the three research papers. The quantitative case-study results are retained as presented in the papers but are interpreted as evidence supporting the broader scientific findings above.

4.2 Research paper 1

This research paper addresses the sustainability-oriented design of RFSCs by jointly considering economic costs, land use, and water use. In line with RQ1, it investigates how multi-objective optimization can be used to quantify trade-offs between these three dimensions and to identify compromise RFSC configurations. The analysis focuses on an EU-wide case study and examines how different sustainability preferences shift technology choices, spatial infrastructure patterns, and the composition of renewable fuel pathways.

To this end, the paper develops a flexible, multi-period, multi-product, and multi-feedstock SC model for renewable fuels in the EU+UK that simultaneously minimizes total system cost, land use, and water use. The resulting multi-objective MILP is solved using the AUGMECON method, generating a detailed Pareto front and a compromise solution that balances economic and environmental objectives.

The key contribution lies in the transferable modeling logic for sustainability-aware RFSC design. The paper demonstrates how land and water indicators can be embedded directly into a network design MILP and how Pareto-efficient alternatives enable transparent, structured reasoning about sustainability trade-offs beyond a single numerical case outcome.

The main finding of the first research paper is that there is a strong conflict between economic and environmental objectives. The payoff matrix shows that optimizing each objective in isolation leads to extreme and mutually conflicting outcomes. The cost-optimal solution (5.89 trillion €) is associated with very high land use (4,595 thousand km²) and large water use (631,329 million tonne), while the land- and water-optimal solutions drastically increase total cost to 160.13 and 121.47 trillion €, respectively.

The Pareto front is well-populated and reveals substantial environmental improvements at moderate cost penalties. Using the AUGMECON method, 110 Pareto-efficient (non-dominated) solutions are obtained. Across the Pareto layer, total system cost varies by +8.4% to +22.8% above the minimum, land use by +0% to +9.6%, and water use by +0.4% to +3.9% above their respective minima. A 9.6% reduction in land use increases cost by 13.3%, and a

3.5% reduction in water use similarly raises cost by 13.3%, illustrating that substantial environmental improvements are achievable with moderate cost increases.

A compromise solution achieves large reductions in land and water use at a modest cost premium. The selected compromise solution increases total system cost by only 10% relative to the cost-optimal case (from 5.89 to 6.48 trillion €), while reducing land use by 80.3% (to 905 thousand km²) and water use by 99.6% (to 2,404 million tonne). This demonstrates that near-optimal environmental performance can be achieved with a relatively small cost premium.

The cost structure is primarily driven by renewable electricity and production technologies. In both cost-optimal and compromise solutions, renewable electricity (solar and wind) accounts for about 38% of total costs, followed by production investments (22–23%) and production O&M (18–19%). Import costs contribute 18–19%, whereas biomass costs remain below 2% in the cost-optimal case and drop to 0.4% in the compromise solution, indicating that land- and water-intensive energy crops can be largely avoided in environmentally oriented designs.

Land and water are not binding at the system level; renewable electricity and imports are key levers. The results show that water is not a limiting resource at the aggregated scale of the case study, and land pressure depends strongly on the chosen point on the Pareto front. None of the solutions are dominated by BtL pathways; instead, PtL and PBtL pathways relying on renewable electricity and CO_2 dominate. All solutions rely on fuel imports to meet 100% demand, with similar import volumes across the Pareto set, underscoring the structural importance of it and the need for import-related infrastructure and policy frameworks.

The case study highlights important policy implications for technology portfolios and infrastructure. Solar and wind capacities must be expanded substantially beyond current levels, with solar becoming particularly critical in compromise solutions. At the same time, investments in production, storage, and transport infrastructure are necessary to use renewable resources efficiently. The model further indicates that imports will remain essential for a stable and feasible RFSC, underscoring the need for long-term import strategies and supportive European policies.

4.3 Research paper 2

This research paper investigates how variability in RES shapes RFSC design, focusing on solar and wind power and the role of imports. Directly addressing RQ2, it applies a TSSP

framework to represent RES variability and evaluate its implications for infrastructure investments and tactical decisions. The analysis explores how explicitly modeling RES variability affects total system costs, technology deployment, and the balance between domestic production and imports.

The RFSC design problem is formulated as a two-stage stochastic MILP that links long-term capacity investments with tactical operations and incorporates both contracted and spot imports. Uncertainty in renewable electricity is represented by 81 country–RES capacity-factor scenarios constructed from 30 years of historical solar and wind data, allowing the model to reflect realistic fluctuations in resource availability.

The paper contributes to uncertainty-aware and flexible sourcing-oriented decision-making by separating investment commitments from operational recourse and by modeling import strategies with differentiated contracting logic. Its central scientific finding is that incorporating renewable electricity variability materially alters the optimal infrastructure portfolio compared with deterministic planning, demonstrating that such variability must be represented explicitly in RFSC design models.

The findings point to RES expansion up to technical potentials, accompanied by strong regional specialization. Under the TSSP solution, solar and wind capacities increase markedly across the EU+UK. Solar power deployment is concentrated in Italy, Spain, and France, while wind capacity is largely built in the UK, Spain, and Germany, with France exhibiting the fastest growth in both technologies. By the final strategic period, RES capacities in most countries approach their permitted potentials, indicating binding renewable resource constraints and underscoring the pivotal role of large-scale RES expansion in RFSC development.

Imports emerge late and, in a fuel,-specific manner. Contracted fuel imports remain limited in early periods (6% of the allowed maximum in T1, 2% in T2, 6% in T3), but rise sharply in T4 to 54% of the total import capacity as domestic RES potentials are exhausted and demand increases. FT fuels dominate this expansion, growing from about 5 million tonne in T3 to 103 million tonne in T4 (92% of the FT-fuel import limit), followed by MeOH imports of 27.5 million tonne in T4 (45% of capacity). H_2 and NH_3 volumes are smaller in absolute terms yet show strong relative growth toward T4. Overall, imports act as a late-stage hedge once domestic renewable resources are nearly fully utilized.

The expected total system cost of the stochastic solution is 10.69 trillion €, with a relatively narrow cost band. The difference between the highest- and lowest-cost scenarios is about

6%. Cost variability is mainly driven by biomass and spot import costs, especially in adverse RES scenarios, but the overall system remains robust due to diversification of technologies and import strategies. Performance evaluation yields a Value of Stochastic Solution (VSS) of 3.4% and an Expected Value of Perfect Information (EVPI) of 4.5%, demonstrating that the stochastic solution outperforms the deterministic one when uncertainty is realized and quantifying the economic value of modeling RES variability explicitly.

Sensitivity analyses highlight that higher spot import prices (3×, 5×, 10× contract prices) trigger shifts toward greater domestic production and feedstock use without causing dramatic cost escalation, indicating that the system can hedge against expensive spot markets via additional RES and production investments. Restricting contracted imports to 10% raises domestic investments and slightly increases total costs, whereas increasing the permissible import share to 30% yields notable cost reductions; further increasing to 50% delivers only marginal additional savings. These results reveal diminishing economic returns from very high import dependence and underline the need to balance cost, security of supply, and geopolitical risks.

The findings have important implications for robust infrastructure planning. The TSSP framework shows that accounting for RES intermittency results in more flexible, but slightly more expensive, infrastructure portfolios than a deterministic one. System robustness is achieved at the expense of potential underutilization of capacities in favorable scenarios, representing a cost of robustness that only pays off under adverse RES realizations. Overall, the analysis highlights that large-scale decarbonization requires both regional specialization in RES deployment and carefully designed import strategies to maintain flexibility under variable renewable availability.

4.4 Research paper 3

This research paper addresses long-term demand uncertainty in RFSC planning and its implications for infrastructure flexibility and investment timing. In line with RQ3, it develops an MSSP model that links strategic and tactical decisions over multiple periods, allowing the SC configuration to adjust as demand information is gradually revealed. The case study investigates how different demand trajectories and learning assumptions influence capacity expansion, technology choices, dependence on imports, and overall system costs.

Building on the previous SC design framework, the paper formulates an MSSP model that represents sequential demand uncertainty over 2021–2060. Demand scenarios are generated using an autoregressive time-series process and reduced via a forward selection heuristic

to construct a tractable scenario tree, enabling investment and operational decisions to adapt at multiple stages throughout the planning horizon.

The paper contributes an adaptive planning formulation for long-horizon RFSC design by modeling demand as an unfolding process and allowing decisions to respond at multiple stages. It further shows how the value of flexibility can be quantified by comparing adaptive strategies against static planning approaches under the same uncertainty assumptions.

The third research paper shows that system costs are largely driven by production and RES investments. The expected total system cost across all scenarios is 2.49 trillion €. Production technologies (investment plus O&M) account for 41.6% of this amount, while RES investments and O&M contribute a further 34.8%, together making up more than three-quarters of total costs. Resources (biomass, water, CO_2) represent 10.0% of costs, spot-market imports 7.6%, and contracted imports 5.8%, whereas storage and transport together account for only 0.2%. These findings underscore that the economic viability of renewable fuels depends chiefly on capital allocation to production facilities and renewable electricity technologies.

Results highlight a temporal concentration of costs in later decades. Costs are strongly front-loaded into the final periods. T3 accounts for 46.0% and T4 for 36.5% of total expenditures, while T1 and T2 contribute only 8.6% and 8.8%, respectively. This pattern reflects rapid demand growth in later decades and the associated need for substantial capacity expansions, underscoring the importance of investment timing and long-term planning under uncertainty.

Analysis reveals a large dispersion of system costs across demand trajectories. Total costs deviate between −13.9% and +41.3% relative to the expected value. High-demand scenarios are up to about 41% more expensive due to intensified import needs and additional infrastructure build-out, whereas low-demand scenarios are roughly 13–14% cheaper. This spread highlights the strong sensitivity of system costs to long-term demand development and confirms that the analysis spans a broad range of plausible outcomes. Results also show endogenous large-scale RES expansion with pronounced regional heterogeneity. To satisfy demand across all scenarios, solar capacity grows drastically from T1 to T4, driven mainly by Spain, Italy, Germany, and France. Wind capacity increases moderately, with major build-out in the UK, Sweden, and Finland. The MSSP solution generates diverse national technology mixes, for example, solar-only expansion in Croatia and Slovakia, and wind-only expansion in Finland, indicating that country-specific policy strategies are more appropriate than uniform EU-wide prescriptions.

The third research paper highlights adaptive investment paths under multi-stage uncertainty. In early stages, installation decisions diverge markedly across demand trajectories, with substantial over- and under-investment relative to expected values; over time, these paths gradually converge as more information becomes available, and RES potentials are approached. The multi-stage formulation thus supports hedging through early diversification followed by adaptive adjustments, capturing the value of flexibility in capacity expansion under uncertain demand. Performance metrics indicate that uncertainty carries a sizable economic penalty, but that MSSP substantially mitigates it. The EVPI of 14.2% quantifies the cost of not knowing future demand, while an RVMSS of 19.4% reflects significant cost savings of the MSSP solution compared with deterministic planning. Together, these results show that multi-stage stochastic planning delivers clear economic benefits for high-dimensional, uncertain energy system design.

This research paper identifies fuel- and resource-specific implications for RFSC development. MeOH and FT-fuels are supplied through diversified strategies that combine domestic production, storage, transportation, and imports, whereas H_2 and NH_3 depend more strongly on domestic production and imports, highlighting distinct infrastructure and policy requirements across fuel pathways. High-demand scenarios increase import reliance and overall costs, while abundant domestic biomass availability markedly lowers system costs by enhancing self-sufficiency. Taken together, the results show that the MSSP framework provides a coherent decision-support tool that links demand uncertainty, technology costs, resource availability, and import strategies in an integrated planning approach.

Chapter 5

5 Conclusion

This dissertation develops an integrated decision-support framework for designing RFSCs that enable the decarbonization of hard-to-electrify transport sectors. The framework employs multi-objective optimization and SP to design flexible, multi-period, multi-feedstock, multi-product supply networks that balance cost and environmental objectives, as well as accounting for key uncertainties in the supply side and demand side of the network. Altogether, this dissertation provides a coherent methodological and empirical basis for understanding how RFSCs can be designed to balance economic efficiency, environmental performance, and robustness under uncertainty. This chapter addresses the dissertation's overarching question by synthesizing insights from Research Papers 1–3 and discussing their implications for renewable fuel supply chain design and policy. The following sections evaluate the research presented in this dissertation. Section 5.1 discusses the methodological and content-wise contribution. Section 5.2 summarizes practical implications for decision-makers involved in planning renewable fuel pathways and infrastructure. Finally, Section 5.3 reflects on the limitations of the dissertation and identifies avenues for future research.

5.1 Contributions and findings

Methodologically, this dissertation contributes a set of complementary optimization models for RFSC design, offering both new model formulations and further developed models that generate deeper insights into the structure and performance of RFSC. First, it presents a multi-objective MILP framework that integrates multiple renewable fuel pathways, feedstocks, and infrastructure components, and minimizes total system cost, land use, and water use simultaneously. The model is solved with an augmented ε-constraint method, yielding a Pareto frontier and enabling a systematic exploration of trade-offs between economic and environmental objectives. Second, the dissertation develops a two-stage stochastic MILP model that explicitly embeds renewable electricity variability into RFSC design. This TSSP model connects long-term investment decisions with short-term operational recourse, using scenario-based representations of solar and wind capacity factors to capture supply-side uncertainty while retaining

practical tractability. Third, the dissertation advances an MSSP framework to represent sequential decision making under demand uncertainty. An autoregressive scenario generation process and a forward scenario reduction are used to construct a scenario tree over several decades, allowing investment and operational decisions to be adjusted as demand evolves. Together, these models demonstrate how multi-objective and stochastic optimization can be employed to design RFSCs that are environmentally oriented and robust to different uncertainties. The proposed framework further facilitates broad future application and analysis of RFSC designs across diverse contexts.

Content-wise, the dissertation provides new insights into the structure and performance of large-scale RFSCs. The multi-objective analysis shows that no single configuration simultaneously minimizes system cost, land use, and water use. Instead, a rich set of Pareto-optimal solutions reveals that substantial reductions in land and water use are achievable at moderate additional cost, and that a carefully chosen compromise solution can drastically reduce land and water requirements relative to a purely cost-optimal configuration. The results also highlight the central role of renewable electricity and production technologies in the cost structure, and show that biomass can be largely substituted by electricity-based pathways when environmental objectives are prioritized.

The stochastic analyses further elucidate how uncertainty shapes RFSC design. Under supply-side uncertainty, the TSSP model emphasizes substantial upfront capital expenditures in renewable electricity and production capacities and reveals strong regional specialization in solar and wind deployment. Contract and spot imports emerge as important flexibility options, particularly in later periods when domestic potentials are nearly exhausted. The TSSP results quantify the economic value of explicitly modeling renewable electricity variability and demonstrate that designs optimized under uncertainty outperform deterministic alternatives when evaluated across scenarios. Under demand uncertainty, the MSSP model shows how optimal capacity expansion paths differ across scenarios and gradually converge as more information about future demand becomes available. The cost distribution across demand scenarios illustrates that high-demand trajectories substantially increase system costs and import dependence, while lower demand reduces expenditure and pressure on domestic resources. The MSSP results quantify the benefits of adaptive, multi-stage planning and show that explicitly accounting for demand uncertainty can lead to considerable cost savings compared to deterministic plan-

ning. Overall, the dissertation contributes both methodological tools and substantive insights that are transferable to other contexts of RFSCs.

5.2 Practical implications

The findings of this dissertation have several practical implications for energy system planners, industry stakeholders, and policy-makers involved in the scaling of renewable fuels. The multi-objective analysis indicates that substantial reductions in land and water use can be achieved with only moderate increases in total system cost. This suggests that environmentally oriented system designs are not necessarily prohibitively expensive and that modest cost premiums can unlock large environmental gains. For practitioners and especially political decision makers, this underlines the importance of explicitly considering environmental constraints in long-term RFSC planning, rather than optimizing solely for cost.

The results also emphasize that renewable electricity and production technologies constitute the dominant cost components of RFSCs. Investments in solar and wind power, as well as in fuel production facilities, account for a large share of total expenditures across all models. This implies that long-term decarbonization strategies should prioritize stable frameworks for financing and deploying renewable electricity and production infrastructure. The results show that regional specialization in solar and wind deployment can exploit spatial heterogeneity in resource quality, while import options provide additional flexibility in balancing domestic potentials and growing fuel demand.

From a planning perspective, the stochastic results highlight the value of designing RFSCs that are robust to uncertain renewable electricity supply and demand trajectories. The TSSP analysis shows that systems optimized under uncertainty exhibit slightly higher expected costs than deterministic designs but perform better across a range of RES scenarios. This can be interpreted as the cost of robustness: additional capacity is built to ensure feasibility and acceptable performance even under unfavorable realizations of renewable availability. Similarly, the MSSP model shows that adaptive capacity expansion strategies that respond to realized demand can reduce expected system costs relative to static designs. For practitioners, this underscores the importance of incorporating uncertainty explicitly in planning processes and of using scenario-based tools to evaluate infrastructure portfolios.

Moreover, the analyses suggest that imports will remain an integral component of future RFSCs. Even in configurations with extensive domestic RES deployment, imports are used to complement domestic production, especially in later periods. This implies that long-term strat-

egies for renewable fuel deployment should consider not only domestic resource assessments but also import infrastructure, contractual arrangements, and associated risks. For policy-makers, the results highlight the need to coordinate domestic production support with policies that facilitate secure and sustainable fuel imports. The insights generated in this dissertation support political decision-makers in making better-informed decisions about the future role of renewable fuels.

5.3 Limitations and future research

The research presented in this dissertation is subject to limitations, which also point to directions for future work. First, the models rely on a range of techno-economic and resource data that are subject to uncertainty and simplifications. While parameter values are based on current literature and empirical sources, future technology costs, efficiencies, and learning effects may deviate from the assumptions used. Similarly, resource availabilities and potentials are represented in an aggregated way, and spatial detail is limited. Future research could incorporate more granular spatial and temporal representations, as well as alternative technology and resource scenarios, to test the robustness of the results.

Second, the modeling framework focuses primarily on economic and environmental objectives, with land use and water use as environmental indicators. Social and broader sustainability dimensions are not explicitly included in the objective functions. Extending the framework to incorporate additional social or distributional objectives would allow a more comprehensive assessment of RFSC configurations and could reveal further trade-offs or co-benefits.

Third, the stochastic models capture uncertainty in renewable electricity supply and fuel demand but do not explicitly represent other important sources of uncertainty, such as technology costs, policy instruments, or global fuel price developments. These factors may significantly influence optimal infrastructure choices and the relative attractiveness of domestic production versus imports. Future work could broaden the uncertainty representation by including additional stochastic parameters or by analyzing alternative policy and market scenarios. At the same time, expanding the uncertainty space would further increase computational demands and may require additional advances in decomposition and solution techniques.

Finally, the case studies are designed to represent a specific European context, including particular assumptions about demand growth, renewable potentials, and import options. While the methodological framework is transferable, the quantitative findings are context-specific and should be interpreted accordingly. Future research could apply models to other regions or to

global systems, compare results across different policy settings, and explore the interactions between RFSC design and other elements of the energy system.

In summary, this dissertation provides a coherent set of methods and insights for designing RFSCs that balance economic efficiency, environmental performance, and robustness under uncertainty. By employing multi-objective optimization and stochastic programming, it lays a foundation for further research and decision support in the transition towards sustainable fuel systems.

Part II: Cumulative Part of The Dissertation

Chapter 6

6 Multi-objective optimization of a renewable fuel supply chain regarding cost, land use, and water use

Authors: Mina Farajiamiri, Jörn-Christian Meyer, Grit Walther

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Abstract

Renewable fuels contribute to net zero emissions by replacing fossil fuels in the transportation sector. Nevertheless, there are significant environmental concerns associated with renewable energy development, including land and water usage. This research explores the use of land and water related to large-scale renewable fuel production. We develop a multi-objective mathematical model to determine the optimal supply chain design for the EU's future renewable fuel demand in the transportation sector. We propose a flexible, multi-period, and multi-stage supply chain design that can accommodate multiple feedstocks and multiple products and that takes the seasonality of the resources into account. We consider economic and environmental impacts by minimizing total system costs, land use, and water use. Based on the analysis of the results, we gain insights into conflicting objective functions and the associated trade-offs and synergies to assist decision-makers in selecting an appropriate framework and gaining a better understanding of future opportunities and impacts of renewable fuel production. The outcome demonstrates that, despite not being a desirable alternative in terms of water and land usage, the utilization of energy crops as raw material has economic benefits. As shown by the results, the burden of such a supply chain lies with renewable electricity requirements that could be the capacity bottleneck and require investments. We find that we could achieve a nearly optimal value of land use and water use by increasing total cost by only 10%.

6.1 Introduction

Taking action against climate change and limiting the rise in global average temperature to 2°C will require significant reductions in carbon dioxide (CO_2) and other greenhouse gas emissions in all sectors (Nations Unies, 2015). CO_2 emissions from fossil fuel combustion in the transportation sector made up 23% of global emissions in 2018. It has been noted that emissions from the transportation sector have been steadily increasing since 2000, interrupted only by the Covid-19 pandemic (IEA, 2022). Since passenger and freight transport demand is expected to increase, defossilizing the transportation sector is essential to achieving emission reduction targets (EEA, 2022). While the electrification of road transport is important, the potential of battery-electric propulsion for heavy-duty vehicles, aviation, and shipping is limited. Therefore, liquid fuels will likely remain in high demand even in the long term (Fasihi et al., 2017). Renewable hydrocarbon "drop-in" fuels, including methanol (MeOH), ethanol, dimethyl ethers (DME), oxymethylene ethers (OMEn), and Fischer-Tropsch fuels (FT-fuels) (diesel, petrol, kerosene) can be used in existing vehicles and distribution facilities without requiring new vehicles or infrastructure. They can reduce the CO_2 emissions of existing internal combustion engine vehicles (Dry, 2002).

FT-fuels can be blended in high contents with fossil fuels. Therefore, they are suitable as a "drop-in" fuel, facilitating market penetration and social acceptance (Schemme et al., 2017). Simultaneously, the role of Hydrogen (H_2) in a low-carbon energy system is well recognized as a new energy carrier for supplying electricity, heat, industry, transport, and energy storage (Abdin et al., 2020). H_2 production is expected to increase dramatically in the future (Wang et al., 2021). Besides, MeOH, like H_2, can also be used as an energy carrier. It has the advantage of being a liquid fuel with a high energy density. It is also relatively safe to handle. MeOH, produced from renewable resources, appears to be an attractive long-term transportation fuel option for reducing greenhouse gas emissions (Olah, 2005). Besides, research studies identified MeOH and H_2 as promising potential carriers to store energy from fluctuating renewable electricity generation (Bos et al., 2020; Yan et al., 2020). Green ammonia might also be a promising renewable fuel option due to its abundance, low carbon footprint, versatility, and stability. It can be synthesized easily from nitrogen and hydrogen, making it readily available and potentially renewable (DNV GL - Maritime, 2019). Moreover, its combustion does not emit carbon dioxide, reducing greenhouse gas emissions and addressing environmental concerns (Sagel et al., 2022; Xing et al., 2021). However, it is also highly toxic, and the existing infrastructure for storage, transportation, and distribution is primarily tailored for industrial applications such as

fertilizers and chemicals. Thus, its widespread adoption is hindered by the need for infrastructure modifications, investments and regulations (Nicola Jones, 2022).

Renewable fuels can, in principle, be produced via various thermochemical and biochemical pathways, which differ in resource consumption, energy efficiency, carbon efficiency, investment, operating costs, and resulting products. In this paper, we focus on the three pathways of Biomass-to-Liquid (BtL), Power-to-Liquid (PtL), and Power-Biomass-to-Liquid (PBtL) for fuel production, which allows us to study different concepts for the utilization of CO_2, biomass, and hydrogen as feedstocks (Albrecht et al., 2017). As long as renewable electricity is used to produce these fuels, they can serve as an alternative to fossil fuels to combat climate change, meet an increase in transportation needs, improve energy security, and help overcome the intermittent nature of renewable energy sources by providing chemical energy storage (Liebich et al., 2021).

Electricity from renewable power generation, carbon sources, and water are all needed to produce renewable hydrocarbon fuels (Albrecht & Nguyen, 2020). Renewable energy sources like wind and solar offer obvious advantages to countries concerned about climate change. From 2005 to 2020, the share of energy from renewable sources used for transport in the EU increased from under 2% to 10.2% (EEA, 2021). Different regions in the world have varying amounts of renewable potential, so a different mix of these energy sources is needed to meet their future energy demands (Teske et al., 2021).

The impact of (inter-)national policies and agreements on renewable energy is transforming the landscape (Enserink et al., 2022). Agriculture, forestry, nature conservation, human settlement, and energy development compete for land, which is becoming an increasingly scarce global resource. So far, land used for energy systems has a comparatively small share (0.4%) of the total land footprint of humanity, which is dominated by agriculture (30-38%), built-up areas (0.5-2.6%), and planted forests (0.9%-1.6%) (Lovering et al., 2022). However, a future energy scenario focusing on deep reductions in greenhouse gas emissions could drastically alter the landscape. In contrast to conventional fuel technologies which harness concentrated energy resources (200-11,000 W_e/m^2), alternative technologies based on renewable resources have power densities several orders of magnitude lower. A typical range of net power density found in literature is 2-10 W_e/m^2 for solar power plants, 0.5-7 W_e/m^2 for large hydroelectric, 0.5-2 We/m2 for wind, and ~0.1 W_e/m^2 for biomass (Capellán-Pérez et al., 2017). Thus, Renewable Energy Sources (RES) use significantly more land for the same amount of energy generation.

It is inherently a trade-off when a piece of land is dedicated to renewable energy, as it cannot be used for food and other usages. Hence, from an environmental perspective, it is important to consider the land that needs to be devoted to new energy infrastructure (Lovering et al., 2022).

CO_2 emissions are only part of the impact of providing energy to 8 billion people. Among the impacts are also water use, material consumption, and local particulate pollution. Recent decades have seen the design of technically feasible energy transition pathways to meet climate goals, but an analysis of how these paths affect water resources is mostly lacking (Jin et al., 2019). It is important to preserve the freshwater ecosystem. The population growth raises serious questions about future water needs in several countries and regions with limited water resources (Postel, 2000). Humanity currently utilizes 26% of total terrestrial evapotranspiration and 54% of accessible runoff (Postel et al., 1996). In agriculture, biomass production for food and fibre consumes about 86% of the freshwater used worldwide (Hoekstra & Chapagain, 2006). There is a close connection between the energy system and water usage. In particular, H_2 production depends heavily on water resources (Howells et al., 2013). Although water consumption for most renewable energy sources (wind, solar, geothermal) is negligible, biomass production consumes significant amounts of water in today's highly competitive markets. It is, therefore, important to consider the amount of water required to produce renewable fuels.

Transparency on trade-offs and research gaps needs to be facilitated by methods and tools that support decision-making processes more efficiently and accurately (Ramos et al., 2022). This paper aims to support the advancement of renewable fuels through supply chain design, modeling, optimization, and analysis. Model requirements can be determined considering the potential environmental effects of the renewable fuel supply chain network. The seasonal availability of renewable resources, land use, and water use on the supply side, and long-term horizon and future demand for promising fuels on the demand side characterize this supply chain network. Various production, transportation, and storage technologies make the supply chain flexible and comprehensive. Investment decisions require the consideration of multi-period models. It is imperative to consider the environmental limits of the supply chain, such as land and water availability, which are linked to geography and topography, to achieve a transition to net zero by 2050. Optimizing this supply chain problem by minimizing land use, water use, and total system cost is critical for climate neutrality and providing transparency on trade-offs.

The organization of this paper is as follows. In Section 2, we review the literature on renewable supply chains and environmental impacts and discuss the novelty and contribution

of this research. Section 3 focuses on our methodology, which includes the detailed problem statement, the mathematical formulation, and the solution method. Chapter 4 discusses a case study of the renewable fuel supply chain for the European Union (EU) and the United Kingdom (UK). Chapter 5 presents the case study results and discussion. Finally, chapter 6 is the conclusion.

6.2 Literature review

In this review, three main topics are discussed. Firstly, we discuss the most critical features of renewable fuel supply chain design. We then discuss the environmental impact studies, followed by a survey of the work that has been done on land and water issues.

Supply chain optimization is a general area of extensive research with a growing number of applications. Matinrad et al. (2013) describe a supply chain as a network of parties working together to satisfy customers. They categorize topics studied within different industrial contexts in their review paper and discover that multi-period multi-echelon supply chains are the most trending issue in this area. A systematic review by Pourhejazy & Kwon (2016) acknowledges that sustainability as the major focus of the modern supply chain is expanding rapidly. According to them, multi-criteria measures have not been adequately addressed. They also conclude that mathematical models are efficient tools for capturing the ever-changing dynamics of supply chain features (Melo et al., 2009). Mathematical models for supply chain design may differ in terms of their network structure, planning horizon, inventory, capacity, production decisions, single or multiple commodities, and more.

The need to phase out fossil fuel production and its associated environmental impact is a major driver for analyzing renewable fuel supply chain networks. A large number of renewable fuel supply chain models focus on single and specific resources or products (Čuček et al., 2014; Malladi & Sowlati, 2018; Yue et al., 2014; Zandi Atashbar et al., 2018). Only a few works address the modeling of multi-commodity and multi-product supply chains (Rentizelas et al., 2009; Wolff et al., 2023). Most of the research so far has focused on a single pathway. They have not considered the flexible supply chain and integration of multiple resources or pathways to produce renewable liquid fuels. Some studies have examined multiple technological pathways for renewable liquid fuels, but they either neglect modeling supply chain aspects or focus exclusively on the energy system perspective (Albrecht et al., 2017; Albrecht & Nguyen, 2020; Quarton & Samsatli, 2020).

Designing supply chains involves deciding what method to use when dealing with complex issues arising from a high level of resolution or a long planning horizon. Time decomposition models are used to deal with the high number of decision variables (Lara et al., 2018; Quarton & Samsatli, 2020). Another significant challenge of renewable energy sources is their seasonal fluctuation, which may be overcome by storing resources. Some studies have considered the seasonality of resources and the deterioration rate of resource storage (Fattahi & Govindan, 2018; Liu et al., 2017; Quddus et al., 2018; You & Wang, 2011). This effect needs to be considered, especially for supply chains with long time horizons which must maintain constant supplies of feedstocks and where dry matter loss poses a risk related to storing materials for a long duration.

Besides, models differ by objective functions. Most of the works consider a single economic objective function that either minimizes the total cost or maximizes profit (Hombach et al., 2018; Osmani & Zhang, 2013; Walther et al., 2012; Wolff et al., 2023; Zhang et al., 2013). Other works have considered environmental impacts as a second objective function as well (Hombach & Walther, 2015; Nguyen et al., 2019; Samsatli & Samsatli, 2018).

Regarding environmental aspects, the literature has addressed renewable fuel supply chains from different points of view. In the context of the growing interest in renewable energy (mainly solar, wind, and biomass), Walker (1995) was among the first to highlight some of the issues that may arise as the use of renewable energy increases. There are some issues outlined in this article, including the land requirements for renewable energy, environmental impacts, and public opposition. In another attempt to address environmental concerns regarding biofuel production, Bernardi et al. (2013) proposed a multi-objective problem to maximize the system's Net Present Value (NPV) as an economic objective function and minimize the water and carbon footprints as the environmental objective functions. Kati et al. (2021) present a wind farm planning strategy prioritizing wildlife protection in Greece. Dhar et al. (2020) present a literature review highlighting reclamation plans for the construction of sustainable energy (wind and solar) plants, considering their negative consequences on the surrounding habitat quality, biodiversity, hydrology, plant makeup, soil stability, and so on. Ponitka & Boettner (2020) present a literature review on the challenges that renewable energies face in competition with nature conservation in Germany to emphasize the importance of monitoring the effects of energy plants on wildlife. Zhong et al. (2018) propose a mixed integer bi-objective optimization to achieve the highest reduction in the greywater footprint of ethanol production at the lowest cost. Fur-

thermore, many other works have considered greenhouse gas emissions as the environmental impact of renewable fuels (Hombach & Walther, 2015; Huang et al., 2019; Samsatli et al., 2015; Sitorus & Brito-Parada, 2022).

Renewable fuel supply chains and RES can have significant impacts on the environment, including land use. Regional and global assessments of decarbonization pathways rarely consider the land footprint of energy. Some works addressed competition between different sectors and the direct and indirect Land Use Change (LUC) effect (Hombach & Walther, 2015; Laborde & Valin, 2012; Nonhebel, 2003; Osmani & Zhang, 2013; Subramaniam et al., 2019). As another approach to consider the land impact of RES, several works have investigated land available for RES as constraints or as scenarios based on different classifications of land (Cintas et al., 2021; Hoogwijk et al., 2009; MacKay, 2013; Quarton & Samsatli, 2020; Samsatli et al., 2015). Although different electricity sources require different amounts of land, only a few studies provide a normalized comparison of their land requirements. Land requirements for RES remain a subject of ongoing debate, with most studies focusing on 100% renewable energy scenarios estimating that the additional land requirements will not be a significant barrier to the transition (García-Olivares, 2016; Cheng & Hammond, 2017; Jacobson et al., 2015; Teske et al., 2015; van de Ven et al., 2021). Garcia & You (2018) note that Life Cycle Optimization (LCO) research often does not consider emissions from LUC and propose a new LCO model that considers the global economy and environment by integrating LUC modeling. Sliz-Szkliniarz (2013) surveys which RES production is more efficient in using land regarding the competition to help investors develop optimal RES portfolios and regulators build public acceptance of RES portfolios. Nazari et al. (2015) attempt to model the land-use competition in Australia between agriculture and renewable energy sources. This paper considers the development of biofuel, bioenergy, livestock, and other processing centers using a multi-stage linear programming model to investigate land use trade-offs. Fthenakis & Kim (2009) address the disparity of RES by presenting normalized land requirements during RES life cycles. They focus on land transformation and land occupation as metrics for analyzing land use of various types of energy, from conventional to renewable. Using the Ecoinvent database, they calculated direct and indirect land transformations for each type of energy and compared land use transformations and occupations. Guo et al. (2016) present a bi-objective MILP model to survey resource-competing bioenergy systems and the effect on the ecosystem caused by land use transitions in response to increasing bioenergy penetration over the 2010s–2050s. They introduce land use intensity to represent the primary production efficiency per unit of available land to incorporate land-com-

peting issues between bioenergy and non-energy systems at different land types. Trondle (2020) explored the relationship between land requirements and the total cost of the renewable electricity systems of different supply-side options for the future of the European energy system using a dynamic model. He calculates land requirements for each system by dividing the installed capacity by capacity density, considering the land requirement for RE as an uncertain parameter. He focused on onshore and offshore wind and ground/roof-mounted photovoltaics (utility-scale and rooftop PV) to meet European demands. Zhang et al. (2021) create a new deep-learning method for analyzing the relationship between urban photovoltaic potential and urban land use in the central area of Wuhan, China, to derive conclusions on future urban planning methods incorporating more PV energy.

Water use is another important environmental aspect of renewable fuels that needs to be considered. Jin et al. (2019) gathered data about water usage in power generation at various life cycle stages. Their study analyzes differences and uncertainties in water use estimates for different types of power generation. Some works have investigated the relationship between water usage and biomass for energy purposes using the concept of water footprint for a different kind of biomass (Drews et al., 2020; Gerbens-Leenes et al., 2008, 2009; Hamilton et al., 2015; Yimam et al., 2015). In this context, several works have investigated water usage in H_2 production processes (Dincer & Acar, 2014; Lee et al., 2019; Mehmeti et al., 2018; Simoes et al., 2021; Turner, 2004). To the authors' best knowledge, there is a lack of work assessing water usage in renewable fuel supply chain optimization problems. Table 6-1 shows an overview of the literature review.

In conclusion, fuel supply chains using RES are complex and dynamic due to a wide range of features. Some measures have already been taken to ensure that the impact of the supply chain on the environment is considered. In particular, the various aspects of land use and water use have been addressed. Despite some studies addressing land use issues as constraints on upgrading or installing RES, the amount of land needed to meet specific renewable fuel demands has not been independently investigated in an integrated optimization model within published literature and databases. The lack of studies on water usage in supply chain optimization problems also needs to be addressed. A new model is needed to comprehensively depict the future development and long-term outlook of the renewable fuel supply chain network, taking into account land and water use as environmental limitations, and other complex features of the supply chain network to provide a better understanding of potential impacts and

optimization opportunities. Therefore, we develop an integrated mathematical model for the future demand for three promising renewable fuels (FT-fuels, MeOH, H_2) considering environmental limitations, including land and water availability for the three major production pathways of BtL, PtL and PBtL and the most important feedstocks (CO_2, water, biomass, renewable electricity). We select two environmental objective functions to minimize the land use and the water use of the supply chain in addition to the economic objective function. It is only through the use of such an integrated model that the full potential of resource efficiency and environmental impact can be discovered. As a result, we can conduct a systemic analysis of alternative decisions based on the optimal Pareto set to determine how to support the transition to renewable fuels most effectively. The model also allows us to determine the potential of countries for producing energy and using renewable resources by considering our criteria and determining the optimal investment for each region according to the available resources and minimum land and water use.

In this study, our focus and contributions revolve around two main aspects. Firstly, we investigate the modeling of a flexible, multistage, multi-resource, and multi-product supply chain. In this regard, we are answering from a modeling perspective to 1a) How can we effectively model the design of a renewable supply chain to accommodate various resources, products, technologies, and time periods with flexibility? 1b) Can we practically handle the numerous assumptions and data inputs required by our approach to effectively answer questions regarding the renewable fuel supply chain? 1c) How can we concurrently consider different performance criteria to optimize the overall functioning and performance of such a network?

Secondly, we delve into the features and challenges specific to the renewable fuel supply chain case study in the EU. The primary research inquiries revolve around the following aspects of the network: 2a) What is the overall cost associated with operating this network and how does it impact the feasibility and sustainability of renewable fuel systems? 2b) How much land is required for the renewable resources integrated into this network and what implications might it have on land use? 2c) What is the direct water consumption involved in hydrogen production and energy crops within the network? 2d) Is there a significant trade-off or compromise in terms of costs when aiming for better environmental results in the context of renewable fuels? 2e) What are the key levers in supply chain design options that can lead to improved economic-environmental compromises? These questions form the central focus of this research.

This paper has different contributions. First, we design a comprehensive, flexible supply chain network to meet the future demand of the transportation sector. Our model is multi-stage, multi-product, multi-feedstock, considers the seasonal availability of resources, and includes the dry mass loss in storage. Secondly, we extend our model to a multi-objective supply chain network design that also addresses environmental limitations. Here we are considering land use of renewable resources and water use of this supply chain besides total costs. As a result, we aim to analyze trade-offs between economic and environmental solutions. Third, the technological advancement of production pathways through time is considered. Finally, we apply our model on the European scale with country-specific granularity. The study facilitates understanding the balance between RES, land use, water use, and the economic impacts of developing renewable fuel supply chains.

Table 6-1: Overview of related works on the land and water issues

REF	Type of Energy	Optimization	Multi-Objective	Land Aspect	Water Aspect	Seasonality	Case Study
(Laborde & Valin, 2012)	Biomass			LUC Emissions			EU
(Zhang et al., 2013)	Biomass	✓		Land Availability			US, EU
(Hombach & Walther, 2015)	Biomass	✓	✓	LUC Emissions			Germany
(Subramaniam et al., 2019)	Biomass			LUC Emissions			Malaysia
(van de Ven et al., 2021)	Solar	✓		LUC Emissions			EU, India, Japan, S-Korea
(Garcia & You, 2018)	Biomass	✓	✓	LUC Emission			US, EU
(Sliz-Szkliniarz, 2013)	Biomass, Wind, Solar			Land Availability			Poland
(Nazari et al., 2015)	Biomass	✓		Land Allocation			Australia
(Fthenakis & Kim, 2009)	Coal, Natural Gas, Nuclear, Hydroelectric, PV, Wind, Biomass			Land Transformation and Occupation			US
(Samsatli et al., 2015)	Biomass	✓	✓	Land Availability		✓	UK
(Quarton & Samsatli, 2020)	CCUS, H2-based Technologies	✓	✓	Land Availability		✓	UK
(Cintas et al., 2021)	Biomass	✓		Land Availability			EU
(Hoogwijk et al., 2009)	Biomass	✓		Land Availability			World
(Guo et al., 2016)	Biomass	✓	✓	Land Availability			UK
(Trondle, 2020)	Solar, Wind, Biomass	✓	✓	Land Required		✓	EU
(Zhang et al., 2021)	Solar (Rooftop PV)			Land-used			China
(Drews et al., 2020)	Biomass				Water Footprint		EU

(Yimam et al., 2015)	Biomass				Water Footprint		US
(Hamilton et al., 2015)	Biomass				Water Footprint		US
(Gerbens-Leenes et al., 2009)	Biomass				Water Footprint		Niederland, Brazil, Zimbabwe
(Simoes et al., 2021)	H_2				H_2 Water Consumption		EU
(Lee et al., 2019)	H_2				H_2 Water Consumption		US
(Mehmeti et al., 2018)	H_2				H_2 Water Consumption		
This Work	Solar, Wind, Biomass	✓	✓	Land use Land Availability	Water Footprint H_2 Water Consumption	✓	EU

6.3 Methodology

This section describes the methodology. The complexity of a supply network optimization problem necessitates using mathematical programming techniques capable of designing and evaluating the network quantitatively and helping investors and decision-makers to evaluate the various scenarios. It has been found that mixed integer linear programming (MILP) is particularly suitable for the optimization of complex networks (Kallrath, 2000). In the following, we will first discuss the problem and design a network following the model structure in detail. Next, we will explore the mathematical formulation. Finally, we will describe the solution method.

6.3.1 Problem setting

Here we discuss the renewable fuels supply chain network designed to fulfill the future demand of the transportation sector in Europe. Figure 6-1 gives an overview of the supply chain, highlighting its structural components without showing the element of time. This representation shows how different elements are interconnected. It is an illustrative example from our case study, showcasing the appearance of the designed supply chain network without time representation. We use the Resource-Technology-Network (RTN) approach introduced by . Samsatli et al. (2015) to represent and flexibly model our problem. Two different types of nodes exist in this approach. The first type (circles in Figure 6-1) represents all the resources ($m \in M$) comprised of raw materials (biomass, CO_2 from point sources, electricity, water), intermediates (CO2 from direct air capture, H_2), and final products (FT-fuels, MeOH, H_2). The second type

of nodes (rectangles in Figure 6-1) illustrates technologies that transform these resources. Additionally, we consider origins of resources ($o \in O$) in our model structure, which consists of biomass of different types ($b \in B$) and sources of renewable electricity ($r \in RE$). For time periods, we use the time aggregation approach based on Samsatli et al. (2015), which helps to reduce the number of periods in long-term planning. In this research, we consider two levels, decadal ($t \in T$) and seasonal ($s \in S$). Each decade consists of n annual periods, and each annual period consists of S seasonal periods. A decadal level is created by aggregating the (n=10) annual periods. Here, we consider a representative year for each decade that is repeated n times throughout the decade. Additionally, we use a cyclic order for seasonal time periods, meaning that the inventory balance for each season is connected to the previous season. Our planning area is divided into several regions ($i \in I$) which have their own specific demand (D_{mits}) and resource potentials (R_{oits}). We consider different production technologies ($p \in P$) and different modes of transportation ($q \in Q$) in this paper. Our study defines a set of transportation modes ($Q_{inv} \subset Q$) that need investments into different pipeline types and capacities. A variety of storage methods ($l \in L$) are considered for different materials. We propose a mathematical formulation for this network, which is built upon previous work by Wolff et al. (2023).

We apply NPV for the calculation of the total cost of the system. Our calculation of land use for renewable electricity generation employs the concept of surface power density as presented by Smil (2010), which explains the relationship between energy carrier and area. Power density means the rate of flow of energy per unit surface area usually expressed in $[W/m^2]$. Energy crop land use has been calculated using crop yields. According to Fischer, a 'crop yield' refers to the amount of grain, or other economic product, harvested per square meter for each crop (usually measured in tons per hectare) (Fischer, 2015). To calculate water needs for consumer products, a measure called “water footprint” was introduced by Hoekstra & Hung (2002), and Hoekstra & Chapagain (2006) developed it further. The water footprint is defined as the annual volume of fresh water used to produce goods and services related to consumption. We use this concept to calculate the amount of water used by energy crops and the amount of water consumed for the production of H_2.

The model adapts to changing conditions through its spatially explicit and dynamic nature and can meet increasing demand over time. Decisions must be taken on both the strategic and the tactical levels. Strategic decisions are taken in each decadal period and present the location, capacity, and number of infrastructures installed in each decade. Thus, these include capital

investments. Tactical decisions instead are taken in each seasonal period (only once per season at the beginning of each decade and are then repeated for the remaining years of the decade) and constitute the rate of production of each production technology, the amounts of transported material, stored material, and resource utilization in each season.

We face a multi-feedstock supply chain that includes water, biomass, wind power, solar power, and CO_2 from direct air capture (DAC), the cement industry, and biogenic point sources as input. We categorize biomass into three types of energy crops, agricultural residues, and forest residues, which differ in land use. Furthermore, wind power is separated into onshore and offshore since they are different regarding power densities and, subsequently, land use. To have a realistic model, we consider the seasonal availability of renewable resources in each region, caused by weather conditions, agricultural cycles, and competition between sectors.

We consider three main pathways in producing FT-fuels and MeOH (BtL, PBtL, PtL). We assume that CO_2 from DAC is only used for the PtL pathway. H_2 can be produced using Alkaline (AEL) or Proton Exchange Membrane (PEM) electrolysis processes. We consider different capacity classes for each production technology, which will be discussed in detail in the case study section. We assume that the technology pathways considered in this research will be in use until the end of the time horizon and the increasing maturity of technologies will decrease investment and operation and maintenance (O&M) costs over time. That way, we are examining the effects of technological advancements over time.

As for transportation, biomass, and final products including H_2, and CO_2 can all be transported by truck, (Cintas et al., 2018; You & Wang, 2011). It is also possible to transport H_2 and CO_2 through pipelines. We regard the pipeline infrastructure for CO_2 and H_2 as initially non-existing and required to be newly installed in this model. We consider different capacities for H2 and CO2 pipelines as well as different types of storage. Due to the seasonality effect, biomass is harvested at a certain point in time, but it is needed all year, so it is necessary to store it. A deterioration rate is assumed for the storage of biomass. Using hydrogen storage is an option in the model to handle fluctuating electricity supplies. To meet fuel demand, we also allow for imports of final products which are produced outside the system boundary.

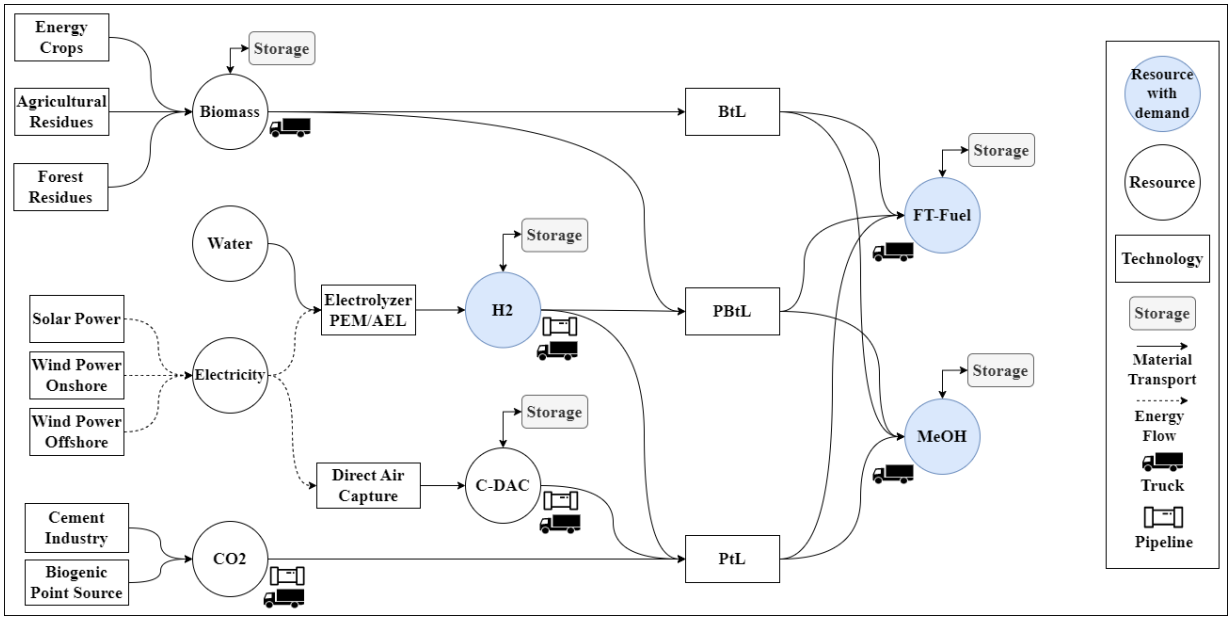


Figure 6-1: Renewable fuel supply chain network

6.3.2 Mathematical formulation

This part presents the mathematical formulation of a multi-objective renewable fuel supply chain network.

6.3.2.1 Nomenclature

$\boldsymbol{I}$	Set of regions	$\boldsymbol{i, i' \in I}$
$\boldsymbol{CI \subset I}$	Set of locations of caverns	
$\boldsymbol{M}$	Set of resources	$m \in M$
$\boldsymbol{O}$	Set of resource origin	$o \in O$
$\boldsymbol{B \subset O}$	Set of types of biomass	$b \in B$
$\boldsymbol{RE \subset O}$	Set of renewable electricity sources	$r \in RE$
$\boldsymbol{T_0}$	Set of planning periods with the start period	$T_0 \sim \{0\} \cup T$
$\boldsymbol{T \subset T_0}$	Set of planning periods	$t \in T$
$\boldsymbol{S}$	Set of seasons, S is a cyclic order	$s \in S$
$\boldsymbol{P}$	Set of production technologies with different capacities	$p \in P$
$\boldsymbol{L}$	Set of storage technologies	$l \in L$
$\boldsymbol{Q}$	Set of transportation technologies	$q \in Q$
$\boldsymbol{Q_{inv} \subset Q}$	Set of transportation technologies with different capacities that require an investment	
Resource/ Demand parameters		
$\boldsymbol{R_{oits}}$	Potential of resource origin o at region i in period t in season s [tonne/season], [MWh/season]	
$\boldsymbol{\vartheta_{isr}}$	Capacity factor for renewable electricity source r in region i and season s [1]	
$\boldsymbol{\Theta_{ir}}$	Maximum installable capacity for renewable electricity source r in region i [MW]	
$\boldsymbol{D_{mits}}$	Demand for resource m in region i in period t in season s [tonne/season]	
$\boldsymbol{\mu_o}$	Share of resource origin o available for transportation fuel production	
$\boldsymbol{\eta_m}$	Deterioration rate of resource m in storage [tonne/season]	

$\boldsymbol{v}$	Maximum share of import for each resource in each decade to each region
Production/ Storage/ Transportation parameters	
$\boldsymbol{\alpha_{mp}}$	Conversion rate (consumption, production) of resource m by production technology p [tonne/tonne], [MWh/tonne]
$\boldsymbol{AY_p}$	Strategic time period in which production technology p is available
$\boldsymbol{\beta_{om}}$	1, if resource m can be obtained from origin o; 0 otherwise
$\boldsymbol{K_p^{prod}}$	Capacity of production technology p [tonne/hour]
$\boldsymbol{K_l^{stor}}$	Capacity of storage technology l per season [tonne/season]
$\boldsymbol{K_q^{tran}}$	Capacity of transportation technology q [tonne/hour]
$\boldsymbol{A_{lm}}$	Resource m that can be stored by storage technology l
$\boldsymbol{B_{qm}}$	Resources m that can be transported by transport technology q
$\boldsymbol{d_{ii'}}$	Distance between region i , i′ [km]
$\boldsymbol{B_{ii'}^{truck}}$	Regions (i, i′) that transportation is possible via trucks
$\boldsymbol{B_{ii'}^{pipe}}$	Regions (i, i′) that transportation is possible via pipelines
Land/ Water related parameters	
$\boldsymbol{L_{itb}}$	Available land for biomass type b in region i in period t [km^2]
$\boldsymbol{L_{itr}}$	Available land for renewable electricity source r in region i in period t [km^2]
$\boldsymbol{\lambda_b}$	Average crop yield of biomass type b [$tonne/km^2$]
$\boldsymbol{\rho_{ir}}$	Surface power density of renewable electricity source r in country i [MW/km^2]
$\boldsymbol{\chi}$	Water footprint of biomass from energy crops [tonne(water)/tonne(biomass)]
Cost related parameters	
$\boldsymbol{\tau}$	Discount rate [1]
$\boldsymbol{\zeta_t^{sp}}$	Discounting factor of each strategic period t [1]
$\boldsymbol{\zeta_t^{yp}}$	Discounting factor of each annual period t [1]
$\boldsymbol{f_p^{prod}}$	Investment cost for production technology p [€/plant]
$\boldsymbol{f_l^{stor}}$	Investment cost for storage technology l [€/storage unit]
$\boldsymbol{f_q^{trans}}$	Distance-related investment costs for transportation technology q [€/km/ transportation infrastructure]
$\boldsymbol{c_p^{pod}}$	Annual O&M cost of production technology p [€/year/plant]
$\boldsymbol{c_l^{stor}}$	Annual O&M costs of storage technology l [€/year/storage unit]
$\boldsymbol{c_q^{trans}}$	Distance-related annual O&M costs of transportion technology q [€/km/year/ transportation infrastructure]
$\boldsymbol{v_q^{trans,dis}}$	Distance-related unit transport costs of transportation technology q [€/tonne/km]
$\boldsymbol{v_q^{tran}}$	Unit transport costs of transportation technology q [€/tonne]
$\boldsymbol{v_{oit}}$	Unit purchasing costs of resource from origin o in region i in period t, [€/tonne] or [€/MWh]
$\boldsymbol{v_{mt}^{import}}$	Cost of importing product m in period t [€/tonne]
Others	
$\boldsymbol{n}$	Number of years per strategic time period
$\boldsymbol{H}$	Number of hours per season
$\boldsymbol{H'}$	Number of operating hours per season
Resource variables	
$\boldsymbol{\omega_{oist}}$	Utilization of resource origin o in region i during period t and season s [tonne/ season], [MWh/season]
$\boldsymbol{\theta_{itr}}$	Installed capacity of renewable electricity source r in region i up to period t [MW]
Production/ Storage/ Transportation/ Import variables	

x_{pist}	Production rate of production technology p in region i in period t during season s [tonne/season]
δ_{pit}	Number of plants of production technology p installed at region i up to period t
y_{lmits}	Amount of resource stored with storage technology l at region i in period t during season s [tonne/season]
γ_{lit}	Number of storage units of storage technology l installed at region i up to period t
$z_{qmii't s}$	Amount of resource m transported from region i to i′ using transportation technology q in period t during season s [tonne/season]
$\kappa_{qii't}$	Number of transportation infrastructures $q \in Q_{inv}$ installed between region i and i′ up to period t
ψ_{mit}^{import}	Amount of material m imported to region i in period t during each season [tonne/ season]
Cost arbitrary variables	
$I_t^{inv,prod}$	Investment cost of production technologies in period t [€]
$I_t^{inv,stor}$	Investment cost of storage technologies in period t [€]
$I_t^{inv,trans}$	Investment cost of transportation technologies in period t [€]
$I_t^{op,prod}$	O&M cost of production technologies in period t [€]
$I_t^{op,stor}$	O&M cost of storage technologies in period t [€]
$I_t^{op,trans}$	O&M cost of transportation technologies in period t [€]
$I_t^{var,trans}$	Variable cost of transportation technology in period t [€]
$I_t^{var,res}$	Variable cost of purchasing resource origins in period t [€]
I_t^{import}	Variable cost of import in period t [€]
Others	
TC	Total cost
TL	Total land used
TW	Total water used

6.3.2.2 Objective functions

This paper aims to minimize three objective functions: total costs, land use, and water use.

Cost minimization objective function:

The total discounted costs of the system consist of 1) the investment cost of installing production, storage, and transportation infrastructures and plants, 2) the operation and maintenance cost of production, storage, and transportation facilities, 3) the variable cost of transportation, 4) the cost of providing resources and 5) the cost of importing. Using a discount rate τ, the cost of each period is transformed into the equivalent value at time t=0 beginning of our time horizon. This approach enables taking the time value of money into account, rather than considering them across different periods.

$$\text{Min } TC = \sum_{t \in T} (I_t^{inv,prod} + I_t^{inv,stor} + I_t^{inv,trans} + I_t^{op,prod} + I_t^{op,stor} + I_t^{op,trans} + I_t^{var,trans} + I_t^{var,res} + I_t^{import}) \quad (6.1)$$

Land use minimization objective function:

For this supply chain network, renewable resources account for most land usage. Therefore, we account for land utilized by renewable electricity installations, i.e., solar power and wind power (onshore and offshore), and by the cultivation of energy crops for biomass raw material. For biomass residues from agriculture and forestry, we assume that land is already dedicated to the production of agriculture and forest products, and utilization of the residues has no further land use implications.

As a measure of land occupation, we use the power density of renewable electricity sources. To calculate the amount of land taken up by these renewable sources, we use the installed electricity capacity required by the fuel supply chain network. The required land area is then derived from power density. The maximum land use through periods is minimized. Our objective function value for land use, therefore, represents the amount of land in the period with the maximum land use. The renewable resource facilities installed in each period are used in subsequent periods, and only infrastructure extensions are allowed. This means that land use for electricity facilities cannot decrease. We calculate the land required for energy crops based on crop yields. The amount of energy crops used by the supply chain network is divided by the average crop yield of energy crops. Unlike renewable electricity sources, the land use of energy crops changes over time if their utilization changes.

$$\text{Min}\, TL \tag{6.2}$$

$$TL = \text{Max}\{\sum_{i}\left(\frac{\sum_{s}\omega_{bist}}{\lambda_{b}} + \sum_{r}\frac{\theta_{itr}}{\rho_{ir}}\right)\}, \qquad b \in \{energy\ crops\}, \qquad t \in T \tag{6.3}$$

Water use minimization objective function:

A high amount of water is used directly in electrolyzers to produce H_2. Due to increasing H_2 demand and population growth that may result in higher water demand in other sectors (e.g., the food industry), taking precautionary measures and trying to control water consumption might be essential. Furthermore, the water footprint of growing the energy crops is taken into account as the direct water consumption of biomass used in this supply chain network. Therefore, as a second environmental impact and third objective function, we minimize the use of water resulting from the electrolysis process and the cultivation of energy crops through the decision variables in this supply chain network.

$$\text{Min } TW = \sum_{t\in T}\sum_{i\in I}\sum_{s\in S}(\omega_{water,ist} + \chi\omega_{bist}), \qquad b \in \{energy\ crops\} \tag{6.4}$$

6.3.2.3 Constraints

In the following, we present the system boundary and constraints of the network.

Balance constraint:

Constraints (6.5) state the resource balance and merge the demand satisfaction requirement with the energy/material balance. Herein, the amount of resource origin utilization ($\omega_{oits}\ \beta_{om}$), resource production ($\alpha_{mp}\ x_{pits}$), net storage of resources considering deterioration ($(1-\eta_m)y_{lmit(s-1)} - y_{lmits}$), net transportation of resources ($z_{qmi'its} - z_{qmii'ts}$) and the amount of imported material from outside the system boundary (ψ_{mit}^{import}) in each region and period should be equal to or higher than the demand (D_{mits}). This constraint ensures that demand is satisfied in all regions and periods for all resources. This part ($\sum_{p\in P|t\geq AY_p}\alpha_{mp}\ x_{pits}$) ensures the installation of mature technologies in each period (t). It is determined by conditioning on the time period and comparing the current period (t) to the year in which technology (p) becomes available (AY_p). If the current time period (t) is equal to or larger than (AY_p) the model has the freedom to select this specific technology (p).

$$\sum_{O\in O}\omega_{oits}\ \beta_{om} + \sum_{p\in P|t\geq AY_p}\alpha_{mp}\ x_{pits} + \sum_{l\in L|(l,m)\in A_{lm}}\left((1-\eta_m)y_{lmit(s-1)} - y_{lmits}\right) + \sum_{i'\in I}\sum_{q\in Q|(q,m)\in B_{qm}}\left(z_{qmi'its} - z_{qmii'ts}\right) + \psi_{mit}^{import} \geq D_{mits}, \qquad m \in M, \quad i \in I, \quad t \in T, \quad s \in S \tag{6.5}$$

Production/Storage/Transportation capacity limitation:

Constraints (6.6) limit the production rate of production technology p to its installed capacity. Constraints (6.7) ensure that the amount of resources stored is equal to or smaller than the installed storage capacity and that resources are only stored in a compatible storage type. Furthermore, it ensures that specific locations exist for storage type 'caverns'. Constraints (6.8) state that the amount of transported resources for those transportation modes that need investment should be equal to or smaller than the installed capacity. Since this only accounts for pipelines, the respective resources can only be transported in regions that can build pipelines between them. Constraints (6.9) ensure that only the correct form of transportation can transport resources.

$$x_{\text{pits}} \leq H' K_p^{prod} \delta_{pit}, \qquad p \in P, \quad i \in I, \quad t \in T, \quad s \in S \tag{6.6}$$

$$y_{lmits} \leq K_l^{stor} \gamma_{lit}, \qquad t \in T, \quad s \in S, \quad (l,m) \in A_{lm}, \; (l = caverns \rightarrow i \in CI) \wedge (l \neq caverns \rightarrow i \in I) \tag{6.7}$$

$$z_{qmii'ts} \leq H' K_q^{trans} \kappa_{qii't}, \qquad q \in Q_{inv}, \quad m \in M, \quad i,i' \in I, \quad t \in T, \quad s \in S \tag{6.8}$$

$$z_{qmii'ts} = 0, \qquad q \in Q, \quad m \in M, \quad i,i' \in I, \quad t \in T, \quad s \in S, \; | \, B_{qm} = 0 \wedge i = i' \wedge B_{ii'}^{pipe} = 0 \wedge B_{ii'}^{truck} = 0 \tag{6.9}$$

Limitation of resource utilization/ import:

Constraints (6.10) limit the utilization of resource origins (i.e., biomass, CO_2 from point sources) to the maximum potential available for the production of fuels for the transportation sector. Constraints (6.11) limit the utilization of wind and solar power to the installed capacity and its seasonal capacity factor multiplied by the hours in a season. Constraints (6.12) limit the installed capacity for solar, wind onshore, and wind offshore power to its maximum installable capacity in each region. According to constraints (6.13), only a portion of demand can be met by importing from outside the system boundary.

$$\omega_{oits} \leq \mu_o \mathrm{R}_{oist}, \qquad o \in O \setminus RE, water, \quad i \in I, \quad t \in T, \quad s \in S \tag{6.10}$$

$$\omega_{oits} \leq H \theta_{itr} \vartheta_{isr}, \qquad o \in RE, \quad i \in I, \quad t \in T, \quad s \in S \tag{6.11}$$

$$\theta_{itr} \leq \Theta_{ir}, \qquad r \in RE, \quad i \in I, \quad t \in T \tag{6.12}$$

$$\psi_{mit}^{import} \leq \upsilon D_{mits}, \qquad m \in M, \quad i \in I, \quad t \in T, \quad s \in S \tag{6.13}$$

Investment extensions constraints:

Constraints (6.14-16) demonstrate that the number of installed production, storage, and transportation facilities is not allowed to decrease over time. Accordingly, constraints (6.17) state that the installed infrastructure for solar, wind onshore, and wind offshore power cannot decrease over time and must remain until the end of the planning period.

$$\delta_{pi(t-1)} \leq \delta_{pit}, \qquad p \in P, \quad i \in I, \quad t \in T_0 \tag{6.14}$$

$$\gamma_{li(t-1)} \leq \gamma_{lit}, \qquad l \in L, \quad i \in I, \quad t \in T_0 \tag{6.15}$$

$$\kappa_{qii'(t-1)} \leq \kappa_{qii't}, \qquad q \in Q_{inv}, \quad i,i' \in I | i \neq i', \quad t \in T_0 \tag{6.16}$$

$$\theta_{i(t-1)r} \leq \theta_{itr}, \qquad r \in RE, \quad i \in I, \quad t \in T_0 \tag{6.17}$$

Land and water constraints:

Constraints (6.18) refer to land availability limitations for energy crops. The amount of biomass utilization for all seasons is divided by the average crop yield of energy crops. The land area calculated this way should be equal to or smaller than the available land for the culti-

vation of energy crops. Constraints (6.19) ensure that the land used for installing solar and wind (onshore and offshore) power should be equal to or smaller than the available land for the installation of solar and wind infrastructure. Used land is calculated by dividing the installed capacity of solar and wind power in each region i by the surface power density. Constraints (6.20) ensure that water used for H_2 production and the cultivation of energy crops should be equal to or smaller than the water available.

$$\frac{\sum_s \omega_{bist}}{\lambda_b} \leq L_{itb}\,, \qquad b \in \{energy\ crops\}\,, \qquad i \in I, \quad t \in T \tag{6.18}$$

$$\frac{\theta_{itr}}{\rho_{ir}} \leq L_{itr}\,, \qquad r \in RE, \qquad i \in I, \qquad t \in T \tag{6.19}$$

$$\omega_{water,its} + \chi\omega_{energycrops,ist} \leq \mu_{water}\mathrm{R}_{water,ist}\,, \qquad i \in I, \qquad t \in T\,, \qquad s \in S \tag{6.20}$$

Cost calculations:

Constraints (6.21) denote the discounting factor for investment decisions taken in the strategic period t, which accounts for the annual period n in each strategic period. Constraints (6.22) ensure that the cost of each year of the strategic period is discounted by multiplying the discounting factor of the strategic period into the sum of discounting factor toward the beginning of the strategic periods for each annual period. Constraints (6.23-25) denote the investment cost for production, storage, and transportation facilities. We calculate investment cost by multiplying the investment cost per facility by the number of facilities installed in the period t and by the strategic discounting factor. Constraints (6.26-28) denote the O&M cost for production, storage, and transportation facilities, respectively, by multiplying the O&M cost per facility by the number of facilities installed up to period t and by the annual discounting factor. Constraints (6.29) account for variable transportation costs with payload-related and distance-related components. Constraints (6.30) denote the cost of resource utilization. Constraints (6.31) illustrate the cost of importing from outside the system boundary.

$$\zeta_t^{sp} = (1+\tau)^{-n(t-1)}\,, \qquad t \in T \tag{6.21}$$

$$\zeta_t^{yp} = \left(\sum_{i=1}^{n}(1+\tau)^{1-i}\right)\zeta_t^{sp}\,, \qquad t \in T \tag{6.22}$$

$$I_t^{inv,prod} = \zeta_t^{sp}\sum_{i\in I}\sum_{p\in P} f_p^{prod}(\delta_{pit} - \delta_{pi(t-1)})\,, \qquad t \in T \tag{6.23}$$

$$I_t^{inv,stor} = \zeta_t^{sp}\sum_{i\in I}\sum_{l\in L} f_l^{stor}\left(\gamma_{lit} - \gamma_{li(t-1)}\right), \qquad t \in T \tag{6.24}$$

$$I_t^{inv,trans} = \zeta_t^{sp} \sum_{i\in I} \sum_{i\prime\in I|i\prime\neq i} \sum_{q\in Q_{inv}} f_q^{trans} d_{ii\prime} (\kappa_{qii\prime t} - \kappa_{qii\prime(t-1)}), \qquad t \in T \tag{6.25}$$

$$I_t^{op,prod} = \zeta_t^{yp} \sum_{i\in I} \sum_{p\in P} c_p^{prod} \delta_{pit}\ , \qquad t \in T \tag{6.26}$$

$$I_t^{op,stor} = \zeta_t^{yp} \sum_{i\in I} \sum_{l\in L} c_l^{stor} \gamma_{lit}\ , \qquad t \in T \tag{6.27}$$

$$I_t^{op,trans} = \zeta_t^{yp} \sum_{i\in I} \sum_{i\prime\in I|i\prime\neq i} \sum_{q\in Q} c_q^{trans} d_{ii\prime} \kappa_{qii\prime t}\ , \qquad t \in T \tag{6.28}$$

$$I_t^{var,trans} = \zeta_t^{yp} \sum_{s\in S} \sum_{i\in I} \sum_{i\prime\in I|i\prime\neq i} \sum_{q\in Q} \sum_{m\in M} (v_q^{trans,dis} d_{ii\prime} + v_q^{tran}) z_{qmii\prime ts}\ , \qquad t \in T\ , \tag{6.29}$$

$$I_t^{var,res} = \zeta_t^{yp} \sum_{o\in O} \sum_{i\in I} \sum_{s\in S} (\omega_{oist} v_{oit})\ , \qquad t \in T \tag{6.30}$$

$$I_t^{import} = \zeta_t^{yp} \sum_{m\in M} \sum_{i\in I} (v_{mt}^{import} \psi_{mit}^{import})\ , \qquad t \in T \tag{6.31}$$

Variable types:

Constraints (6.32-34) denote the type of variables.

$$\theta_{itr} \geq 0, \qquad i \in I\ , t \in T_0, r \in RE \tag{6.32}$$

$$z_{qmii'ts}, x_{pist}, y_{lmits}, \omega_{oist}, \psi_{mit}^{import} \geq 0\ , \quad q \in Q, p \in P, l \in L, m \in M, o \in O, i, i' \in I, t \in T, s \in S\ , |i \neq i' \tag{6.33}$$

$$\kappa_{qii\prime t}, \delta_{pit}, \gamma_{lit} \in \mathbb{N}_0\ , \qquad q \in Q_{inv}, p \in P, l \in L, i, i' \in I, t \in T_0, |\ i \neq i' \tag{6.34}$$

6.3.3 Solution method (AUGMECON)

In this work, the multi-period, multi-objective Mixed Integer Linear Programming (MILP) optimization problem is solved using the augmented ε–constraint method (AUGMECON), which results in an efficient Pareto optimal frontier.

In the ε–constraint method, one of the objective functions is optimized by incorporating other objective functions as constraints. We can solve the problem by varying the right hand side of the constrained objective functions. In the traditional ε–constraint method, an optimal solution is considered efficient only if there is no further improvement possible in one of the $(n-1)$ constrained objective functions. Otherwise, if there are alternative optimal solutions (that may improve one of the constraints that correspond to (n-1) objective function), the obtained optimal solution of traditional ε–constraint is not efficient but is a weakly efficient solution. Thus, traditional ε–constraint method does not guarantee the efficiency of the obtained solution, especially in circumstances with more than two objectives (Khorram et al., 2014).

This issue has been addressed by the application of the augmented ε–constraint method that was first developed by Mavrotas (2009). Mavrotas suggested a solution to address this ambiguity by introducing non-negative slack variables and transforming the inequality constrained objective functions of the conventional ε-constraint method into equality constraints. Simultaneously, these slack variables are incorporated into the objective function (with lower priority in a lexicographic manner) to guarantee the attainment of efficient solutions. Equations (6.35) depict the improved augmented ε–constraint method where e_i are the right-hand side parameter for the specific iteration drawn from the grid points, r_i are the ranges of the respective objective functions, s_i are the slack variables of the respective constraint, and eps is a small number between $[10^{-6}, 10^{-3}]$. Numerous researchers have employed the augmented ε–constraint method to obtain efficient solutions to multi-objective optimization problems in general (Aghaei et al., 2011; Du et al., 2014; Nezhad et al., 2014), as well as supply chain optimization problems specifically (Razmi et al., 2013). This paper uses this improved augmented ε–constraint method to solve the multi-objective MILP problem and obtain the Pareto frontier.

$$\begin{aligned} &Min\ \left(f_1(x) - eps\left({}^{s_2}/_{r_2} + \cdots + {}^{s_n}/_{r_n}\right)\right) \\ &st: f_2(x) + s_2 = e_2\ , \ldots \\ &f_n(x) + s_n = e_n\ , \\ &x \in S\ , \qquad s_i \in \mathbb{R}^+ \end{aligned} \tag{6.35}$$

We chose the augmented ε-constraint method (AUGMECON) for several reasons. Firstly, our research aims to highlight the trade-offs between conflicting objective functions, aligning with the compromise and trade-off emphasis of the Pareto method. Secondly, the ε-constraint method, known for its simplicity, explicit constraint handling, trade-off exploration capability, well-known solution space, and computational efficiency, served as the main approach (Zhang & Reimann, 2014). To enhance effectiveness, the augmented ε-constraint method (AUGMECON) was selected as an improved version, offering advantages such as thorough solution space exploration, capturing diverse trade-offs and preferences, and excelling in handling complex optimization problems with multiple objectives, constraints, and preferences (Mavrotas, 2009; Mavrotas & Florios, 2013). AUGMECON's objective is to find Pareto optimal solutions, presenting decision-makers with a comprehensive range of options that represent the best possible trade-offs between objectives**.** In our research, this is in line with our aim to offer decision support for policymakers and investors regarding the development of renewable fuel supply chains and enhancing transparency in the face of conflicting targets.

The augmented ε-constraint method (AUGMECON) has potential biases and limitations. It assumes easily quantifiable trade-offs using constraints, which may be challenging in complex problems. Biases can arise from prioritizing one objective over others and small changes in constraint definitions (Zhang & Reimann, 2014). To mitigate biases, careful problem formulation, thorough trade-off evaluation, and a lexicographic method for calculating right hand side values are employed.

In this paper, we solve the multi-period multi-objective MILP optimization problem using the augmented ε-constraint method with Python/Gurobi, which results in an efficient Pareto optimal frontier.

6.4 Case study

We apply our model and method to a country-specific European case study to fulfill the future demand of the transportation sector with the time horizon of 2020 to 2060 in line with achieving climate neutrality by 2050. We divide the time horizon into strategic periods of ten years. As a result, we have four strategic periods in which investment decisions are taken at the beginning of each decade (T1: 2020-2030, T2: 2031-2040, T3: 2041-2050, T4: 2051-2060). We also consider four seasons (spring, summer, autumn, and winter) in a year to represent the seasonal availability of the resources. We assume that spring is defined as the period from March to May, summer from June to August, autumn from September to November, and winter from December to February. Operating hours for production and transportation facilities in each season, assuming an 80% capacity factor with no spares, are 1752 hours (Larson et al., 2009). The geographic scope includes the 27 countries of the EU and the UK. This case study aims to demonstrate the effectiveness of the proposed research method and simulate future conditions in Europe. Due to the increasing water utilization in European countries, it is important to look into the water use impacts of future fuel systems to avoid potential water stress (EEA, 2018). The same holds for land use as well. We use a discount rate of 3.5% per year based on Quarton & Samsatli (2020) for all the cost calculations.

We assume that there are no existing fuel production facilities at the beginning of the planning horizon. The supply potential of CO_2 point sources is assumed based on Siegemund et al. (2017). For the supply potential of the three biomass types, we rely on the ENSPRESO (Energy System Potentials for Renewable Energy Sources) database, which is an open database that estimates the potential energy produced by renewable energy systems (solar, biomass, wind) throughout Europe over 2010-2050 based on a wide range of other references, models,

and data (Ruiz et al., 2019). We use ENSPRESO's reference scenario for biomass supply in each region and decade. In addition, the seasonal availability of biomass is calculated by allocating the quantities of individual biomass products to their harvest period based on Čuček et al. (2014). We assume that available forest residues and agricultural residues are limited to 28% and 40% of their potential based on Cintas et al. (2018) and Haase et al. (2016), due to the fact that not all biomass could be used for the transportation sector. For solar and wind power (onshore and offshore), we use the reference scenario from ENSPRESO to determine the maximum installable capacity and the capacity factors of solar and wind power (onshore and offshore) in each country. In this case study, we assume that freshwater is used for H2 production and the cultivation of energy crops, and freshwater potential in each country is based on the Eurostat database (European Commission, 2022). Figure A 6-1 in the appendix shows the availability of resources in different countries.

As mentioned above, we consider BtL, PBtL, and PtL technologies for producing FT-fuels and MeOH, and PEM and AEL electrolyzers for producing H2. Their techno-economic and cost data are based on the FVV study (Report, 2021) and Vos et al. (2020). We have considered three capacities and related costs for each technology based on the FVV study. The smallest capacity is assumed to be available at the beginning of the first strategic period. In contrast, the two higher capacities will be available from the second and fourth strategic periods, respectively. Thus, we are considering technological advancement, which means improving technology features such as cost performance and capacity over time. This does not include DAC technology, for which we only consider one capacity throughout the time horizon. Table A 1 in the appendix shows the techno-economic data for all production pathways. Resource inputs for these production technologies are taken from Liebich et al. (Liebich et al., 2021) and are shown in Table A 6-2 in the appendix.

We consider two different capacities for CO_2 pipelines with related costs based on Fasihi et al. (2019) and McCollum & Ogden (2006). Three different capacities with related costs are considered for the transportation of H2 based on the planned European Hydrogen Backbone (EHB) initiative (Wang et al., 2020). Although current natural gas pipelines can be repurposed to be used for H2 transportation, we are only considering new pipelines based on EHB data (Wang et al., 2020). The reason is that, based on this study, a large part of today's natural gas pipelines are small pipelines that are unsuitable for long-distance transportation and have a higher O&M cost. Furthermore, the availability of existing natural gas infrastructure in the long

term is still discussed and depends on factors like future market developments and regulations. In this study, all pipelines need investment, and strategic decisions have to be taken on where, when, and in which capacity to install. The haversine function which determines the great-circle distance between two points on a sphere given their longitudes and latitudes was used to calculate distances between country centroids for transportation. Transportation data are available in Table A 6-3 in the appendix.

Biomass, CO_2 from DAC, H2, FT-fuels, and MeOH can be stored in this network. Caverns are considered for storing H2 in only a few countries (Bulgaria, Germany, Denmark, France, Netherlands, Poland, Portugal, UK). In this case study, we have considered an average deterioration rate of 0.123 $[tonnes/season]$ only for biomass, since deterioration is negligible for the other resources compared to biomass. Storage data is available in Table A 6-4 in the appendix.

As mentioned in our mathematical formulation, the amount of land required for biomass, solar, and wind power has to be equal to or smaller than the available land. Available land for biomass is calculated based on the ENSPRESO database using the reference scenario, which provides two sectors for available land (agriculture and forestry). We also use the reference scenarios of the ENSPRESO database for solar and wind power. Figure A 6-2 in the appendix shows the available land in the respective countries. We need their surface power densities to calculate the land used for installing solar and wind power (onshore and offshore). Due to the fact that we observe a variety of values in the literature with different assumptions, as well as a need to remain consistent with the data used, we calculated the surface power density by dividing the installable electricity capacity potentials by the land available in each country based on the ENSPRESO database. Table A 6-5 in the appendix contains surface power density data. For land dedicated to energy crop cultivation, we use the average power density of energy crops based on van Zalk & Behrens (2018) to calculate an average crop yield. For this calculation, we also need the Lower Heating Value (LHV), which we obtain by averaging the LHV values introduced in the ENSPRESO database for products in the energy crop category.

European demand for renewable liquid fuel is expected to increase in the future. In this case study, the demand for FT-fuels is based on the high-demand scenario of Siegemund et al. (2017). H_2 demand is calculated based on an EHB study by summing up the demand for H2 in aviation and heavy-duty road transport (Wang et al., 2021). Since we could not find a suitable study on the future demand for MeOH in the transportation sector, we considered the IRENA

projection (IRENA, 2016) for global demand for MeOH in each of the decades. The share of European countries from global MeOH consumption is 10%, and fuels directly account for 34% of it (Alvarado, 2016). Hence, we assume that MeOH demand might be higher than in the transportation sector. It is noteworthy that each country's demand for FT-fuels, MeOH, and H_2 was calculated based on the population of each country. Demand data can be found in Table A 6-6 in the appendix. It is also possible to satisfy demand by importing from other, not further specified countries outside the EU and the UK. We follow the assumption of the FVV study that only 30% of the demand in Europe should be met by imports from other countries in order to achieve independency in energy provision, and to account for the limited available amount of imports. Based on this work and using interpolation, the import cost is determined and shown in Table A 6-7 in the appendix (Report, 2021).

Each resource has a price as well as expected price developments over the time horizon. We calculate biomass price based on the reference scenario of the ENSPRESO database. The price of the water supply was extracted from the governance of European water services (EurEau, 2020). The price for supplying CO_2 from industry and biogenic sources is based on Brynolf et al. (2018). Finally, the price of electricity provided by solar and wind power without taxes and grid fees is based on Searle & Christensen (2018). All price data are available in Table A 6-8 and Table A 6-9 in the appendix.

In each iteration of the model, there are a total of 931,715 variables, with 21,450 being integers, and 489,062 constraints. To ensure timely results, we have set a max gap of 0.02 and imposed both soft and hard time limits of 5,000 and 20,000 seconds, respectively. The runtime of each iteration may vary depending on the epsilon values (RHS) of the AUGMECON method. The model is being solved using an Intel(R) Core (TM) i7-8700K processor @ 3.70GHz, with 3696MHz, 6 cores, and 12 logical processors on a PC.

The overview of all the data used as parameters of our model in this case study is provided in Table 6-2.

Table 6-2: Data description

Description	Symbol	Unit	Source
Demand	D_{mits}	[tonne/season]	FT-fuels: (Siegemund et al., 2017) H_2: EHB (Wang et al., 2020) MeOH: (Alvarado, 2016; IRENA, 2016)
The potential of resource origin	R_{oits}	[tonne/season]	Biomass: (European Commission, 2019a) CO2: . (Siegemund et al., 2017)

			Water: (European Commission, 2022)
Maximum installable capacity for electricity generation	Θ_i^{solar} Θ_i^{windon} $\Theta_i^{windoff}$	[MW]	Solar Power: (European Commission Joint Research Centre, 2019b) Wind Power: (European Commission, 2019c)
Capacity factor	ϑ_{is}^{solar} ϑ_{is}^{windon} $\vartheta_{is}^{windoff}$	[1]	Solar Power: (European Commission Joint Research Centre, 2019b) Wind Power: (European Commission, 2019c)
The conversion factor of resource m by production technology p	α_{mp}	[tonne/tonne], [MWh/tonne]	(Liebich et al., 2021)
Capacities	K_p^{prod} K_l^{stor} K_q^{tran}	[tonne/hour], [tonne/season]	Production technology: (Liebich et al,, 2021), Analogues (Report, 2021) Storage technology: (Akhtari et al. 2018; Report, 2021; Reuß et al., 2017) Transport technology: (Fasihi et al., 2019; McCollum & Ogden, 2006; Wang et al., 2020)
The period that production technology p is available to be installed	AT_p	_	(Report, 2021)
Deterioration rate of resources	η_m	[tonne/season]	Biomass: (Xie et al., 2014; You & Wang, 2011)
Available land	L_{it}^{bio} L_{it}^{solar} L_{it}^{wind}	[km^2]	Biomass: (European Commission, 2019a) Solar Power: (European Commission Joint Research Centre, 2019b) Wind Power: (European Commission, 2019c)
The lower heating value	LHV_b	[MJ/kg]	(European Commission, 2019a)
Power densities	$\rho_b^{bio}, \rho^{solar}$ ρ^{windon} $\rho^{windoff}$	[MW/km^2]	Biomass: (van Zalk & Behrens, 2018) Solar Power: (European Commission Joint Research Centre, 2019b) Wind Power: (European Commission, 2019c)
Investment costs and annual O&M cost	f_p^{prod},c_p^{prod} f_l^{stor}, c_l^{stor} f_q^{trans},c_q^{trans}	[€], [€/km], [€/km/year]	Production technology: (Liebich et al., 2021), Analogues to (Report, 2021) Storage technology: (Akhtari et al., 2018; Report, 2021; Reuß et al., 2017) Transport technology: (Fasihi et al., 2019; McCollum & Ogden, 2006; Wang et al., 2020)
Distance-related unit transport costs	$v_q^{trans,dis}$	[€/tonne/km]	(Leduc, 2009; Reuß et al., 2017; Wolter, 2021)
Unit transport costs of transport technology	v_q^{tran}	[€/tonne]	(Fasihi et al., 2019; Leduc, 2009; McCollum & Ogden, 2006; Reuß et al., 2017; Wolter, 2021)
Unit purchasing costs of resource	v_{oit}	[€/tonne], [€/MWh]	Biomass: (European Commission, 2019a) Water: (EurEau, 2020; Varone & Ferrari, 2015) CO_2: (Brynolf et al., 2018) Solar: (Searle & Christensen, 2018) Wind: (Searle & Christensen, 2018) Import: (Report, 2021)

6.5 Results

This section will discuss the results for the Pareto frontier, each of the three objective functions separately, the results of the multi-objective MILP problem, and trade-offs.

We first optimize each of the objective functions associated with cost, land use, and water use separately without taking into account the other two objective functions, in order to demonstrate the efficiency of the results of considering the multiple objectives model and the effectiveness of our approach. Table 6-3 demonstrates the values of each separate objective function, known as the payoff matrix. "Cost-optimal solution" illustrates the values obtained by optimizing single-objective models with cost as the objective function. In the same way, "land-optimal solution" and "water-optimal solution" show the values we obtain from optimizing the single-objective model with land use and water use as objective functions, respectively. The cost objective function has its highest value in the land-optimal solution and vice versa. Furthermore, water use has the highest value in the land-optimal solution.

Table 6-3: Payoff matrix, the optimal value of each objective function independent of other objectives

	Cost value (trillion €)	Land use value (thousand km^2)	Water use value (million tonne)
Cost-optimal solution	5.89	4,595	631,329
Land-optimal solution	160.13	879	8,312,471
Water-optimal solution	121.47	4,168	2,313

Figure 6-2 compares the development of total land used over time for the cost- and land-optimal solutions. It can be seen that amount of land use in each decade increases. The land use of the last period in the cost-optimal solution is 5 times as high as the land-use in the land-optimal solution.

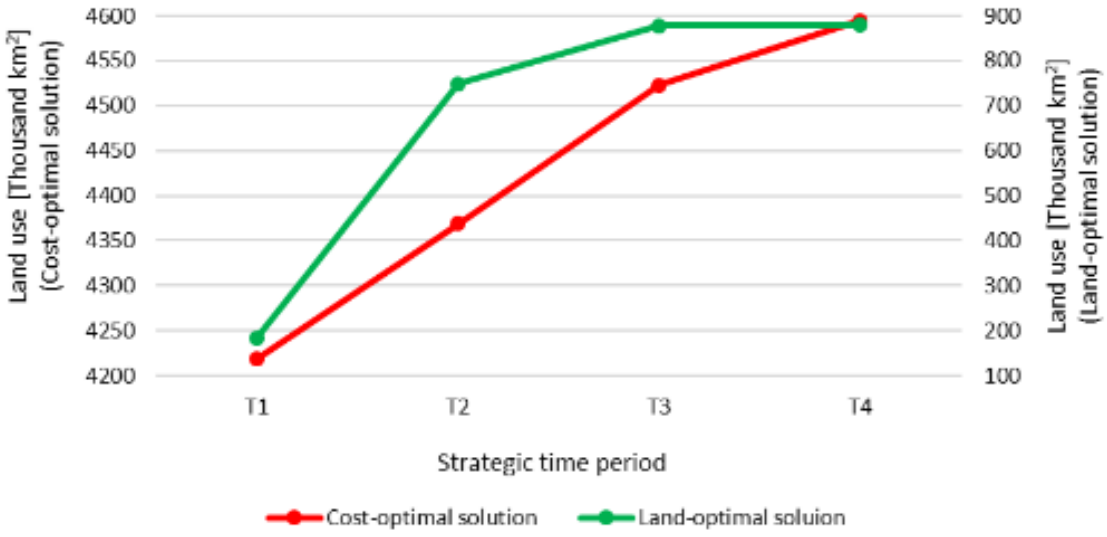


Figure 6-2: Comparison of the development of total land use obtained by the cost-optimal and land-optimal solutions over the planning horizon

Table 6-4 compares the values of water used in each strategic period for the cost-optimal solution and its optimal value for the water-optimal solution. The result shows that energy crops are not used in the water-optimal solution to remove the water footprint of crop cultivation and minimize water use. As is evident in the cost-optimal solution, most water use is for energy crops in the last two periods.

Table 6-4:Comparison of the optimal values of water used obtained by the cost-optimal and water-optimal solutions in each strategic period

	Cost-optimal solution		**Water-optimal solution**	
Strategic time period\ Water amount [million tonne]	Energy crops	H_2 production	Energy crops	H_2 production
T1	31,176	90	0	55
T2	122,516	255	0	253
T3	215,985	813	0	829
T4	259,365	1,129	0	1,175

Figure 6-3 shows a Pareto-optimal frontier derived as dominating solutions from the AUGMECON method. In this figure, the three axes represent the values of the three objective functions. It provides an overview of the trade-offs between the objectives and non-dominated solutions. It also shows that no single solution set simultaneously minimizes all three objective functions. We run the program for AUGMECON for 121 iterations with different epsilon values and record the respective solutions. For the considered example, the method results in 110 solutions. We can conclude from this figure that AUGMECON is able to find solutions that have

a range of objective function values of [+8.4%, +22.8%] above the absolute minimum feasible total costs, [+0%, +9.6%] above the absolute minimum land use and [+0.4%, +3.9%] above the absolute minimum for water use. We will, later on, introduce and discuss a compromise solution that is already depicted in Figure 6-3.

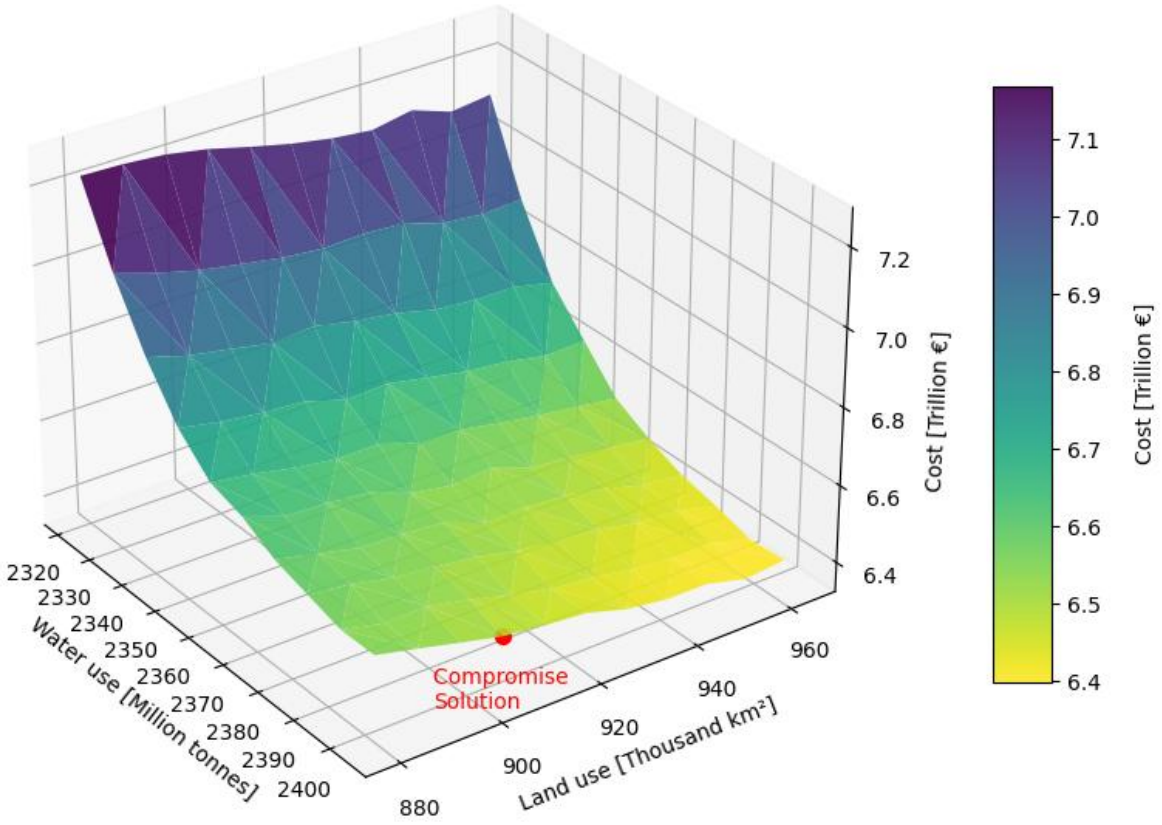


Figure 6-3: Pareto-efficient layer

An illustration of the trade-off between pairs of objective functions is provided in Figure 6-4 and Figure 6-5, with colors and color bars representing the value of the third objective function. The points with the same color have the same value for the third objective function while showing the changes for the other two objective functions. As can be seen, across each level of water use value, there are trade-offs between cost and land use. A 9.6% decrease in land use increases the cost by 13.3% (Figure 6-4). Similarly, with different values of land use, decreasing water use by 3.5%, the cost only increases by 13.3% (Figure 6-5). As a result, we find that there is a noticeable reduction in costs at different levels of land use value with a only slight increase in water use.

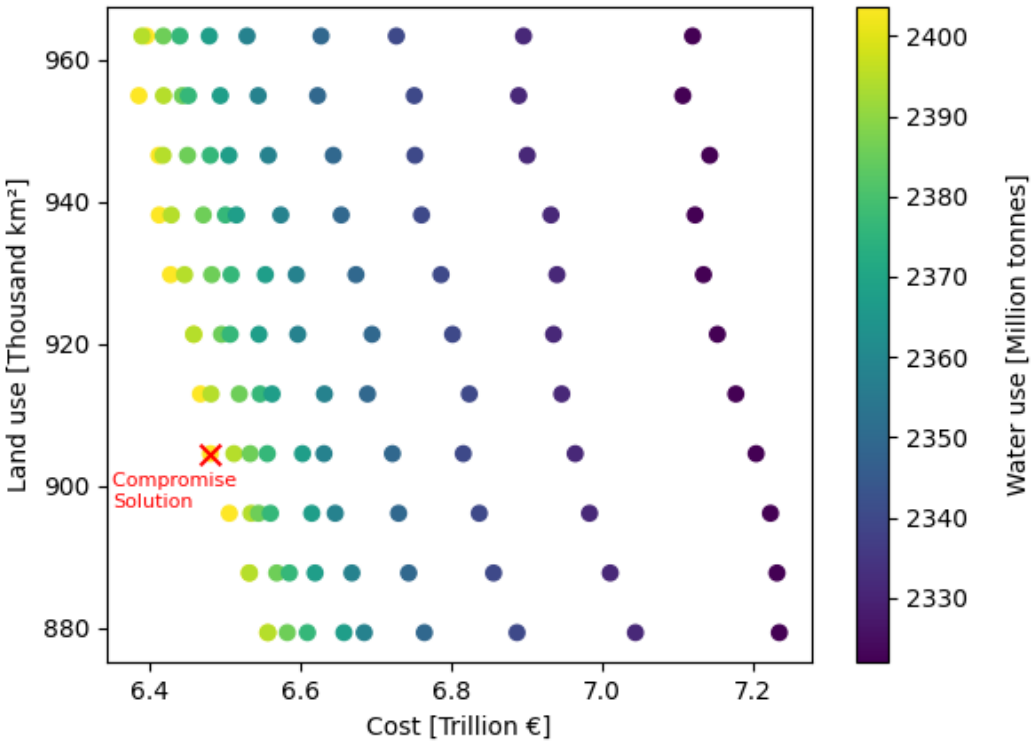


Figure 6-4: Trade-offs between cost and land use. Water use is shown by the color and the color bar

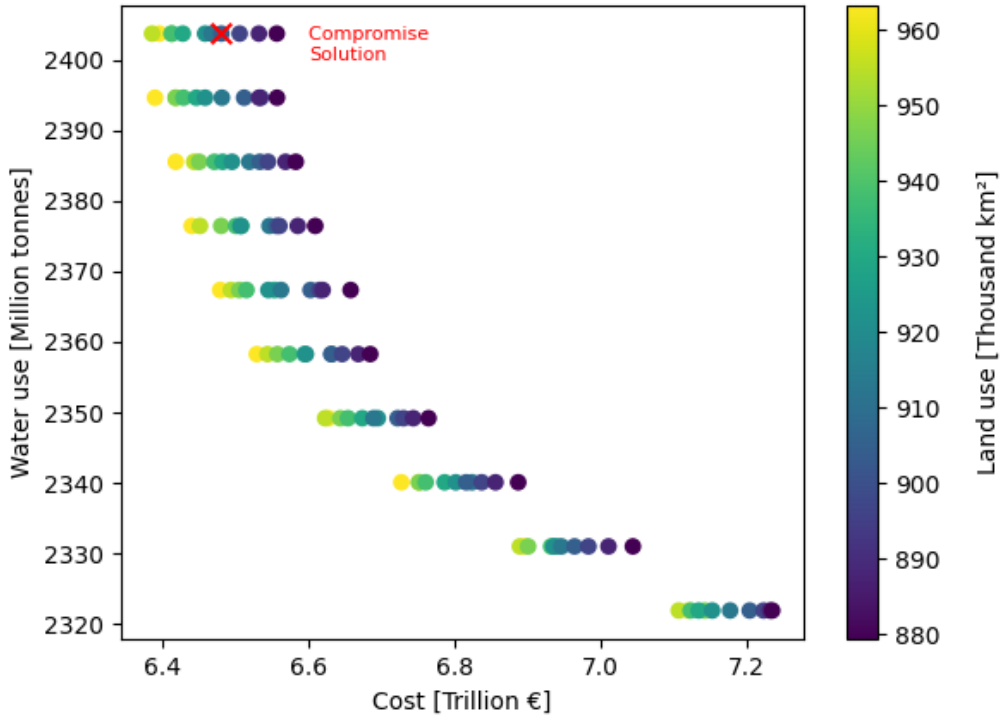


Figure 6-5: Trade-offs between cost and water use. Land use is shown by the color and the color bar

According to the results, no single solution is optimal in all three objective functions. Due to this, we select a compromise solution from the Pareto frontier that seems promising (Table 6-5). To achieve a compromise solution, we increased the optimal cost value by 10% (resulting in 6.48 trillion €). After analyzing AUGMECON's options, we selected a solution with this cost value that is closely aligned with optimal land and water use values while deviating from the optimal cost value by only 10% as a compromise solution. By examining this compromise solution from the Pareto-frontier, we see that water use can be strongly reduced by 99.6% and land use by 80.3%, with only a 9.98% increase in cost over the optimal-cost solution. We compare the strategic decisions (i.e., number, capacity, locations of production and storage facilities, installed transportation infrastructure, and the installed capacity of renewable electricity in each country) of the cost-optimal and compromise solutions in the following.

Table 6-5: Compromise solution selected from Pareto-frontier

	Cost value (trillion €)	Land use value (thousand km^2)	Water use value (million tonne)
Solution from Pareto frontier	6.48	905	2,404

Table 6-6 compares the cost structure in the cost-optimal and compromise solutions. Both solutions have a similar cost structure. Renewable electricity generated by solar and wind power accounts for 38% of the total costs in both solutions. Investment cost of production accounts for 22% and 23%, import cost accounts for 19% and 18%, and production technologies O&M cost account for 18% and 19% of total costs in the cost-optimal and compromise solutions respectively. In the cost-optimal solution biomass cost accounts for 2% of the total costs, whereas this percentage in the compromise solution is only 0.4%.

Table 6-6: Cost structure of the cost-optimal and compromise solutions

Cost items [million €] \ Strategic time period	Cost-optimal solution		Compromise solution	
	Value	Share	Value	Share
Biomass cost – agricultural residues	7,403	0.13%	7,463	0.12%
Biomass cost – forest residues	14,591	0.25%	16,227	0.25%
Biomass cost – energy crops	91,380	1.55%	0	0.00%
CO_2 cost – biogenic point sources	14,305	0.24%	16,649	0.26%
CO_2 cost – cement industry	12,972	0.22%	13,069	0.20%
Electricity cost from solar power	2,026,745	34.40%	2,001,791	30.89%
Electricity cost from wind power	204,183	3.47%	477,005	7.36%
Import cost	1,123,998	19.08%	1,141,008	17.61%
Investment cost of production	1,268,028	21.52%	1,504,771	23.22%
Investment cost of storage	1,910	0.03%	1,672	0.03%
Investment cost of transportation	4,891	0.08%	5,122	0.08%
O&M cost of production	1,084,106	18.40%	1,259,484	19.44%

O&M cost of storage	651	0.01%	583	0.01%
O&M cost of transportation	3,152	0.05%	2,310	0.04%
Unit transportation cost	10,870	0.18%	6,617	0.10%
Water cost	23,105	0.39%	26,501	0.41%

Figure 6-6 shows the land use for energy crops, solar, and wind power (onshore/offshore) in each period for the cost-optimal and compromise solutions. In the cost-optimal solution, land allocated to biomass and, more specifically, to energy crops increases over time. However, the land used for renewable electricity resources remains the same in all periods. This result shows that essential renewable electricity infrastructure is already installed at the beginning of the planning horizon, and the increasing demand over time is covered by biomass as an economical option. In the compromise solution, land used for solar power increases over time, since it has the highest power density. In this solution, no land is allocated to energy crops, hence, the model removes the land used and water used for energy crops to decrease these objective functions. However, upfront investment into solar power, thus the economic objective value increases. Although energy crops are heavily used in the cost-optimal solution, they are not used in the compromise solution. This result demonstrates that energy crops are a valuable resource for maintaining a cost-optimal supply chain. However, not using energy crops increases costs only by 10%, while improving land use and water use objectives significantly.

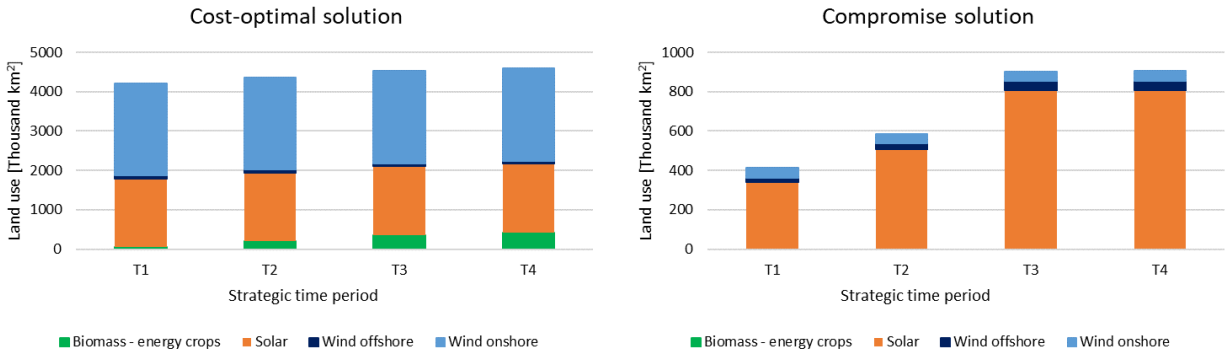


Figure 6-6: Land use in the cost-optimal and compromise solutions

Table 6-7 shows the water used in the cost-optimal and compromise solution. The amount of H2 produced in the cost-optimal and the compromise solution respectively, is 243 and 265 [million tonne].

Table 6-7: Water use in the cost-optimal and compromise solutions

	Cost-optimal solution		**Compromise solution**	
Strategic time period \ Water amount [million tonne]	Energy crops	H_2 production	Energy crops	H_2 production
T1	31,176	90	0	86

T2	122,516	255	0	275
T3	215,985	813	0	850
T4	259,365	1,129	0	1,192

Figure 6-7 and Figure 6-8 show an overview of the land used for renewable resources and the share of each production technology to produce fuels in each country in the cost-optimal and compromise solution respectively.

Figure 6-7 illustrates how much land each renewable electricity resource (solar and wind onshore/offshore power) occupies within the last period. In the pie charts, the size shows the installed capacity of renewable electricity in each country in the last period. The total land use and installed renewable electricity over all countries are represented by the large pie chart in the top left corner of each figure. In the cost-optimal solution, wind onshore power takes up 51.2% of the land utilized for renewable electricity resources, solar power takes up 38.1%, and offshore wind power uses 1.4%. The compromise solution, however, favors solar power as the dominant land use factor, accounting for 89.3% of the land utilized for renewable electricity resources, and wind onshore/offshore power take up 5.3% and 5.4% respectively. It is interesting to note that in the cost-optimal solution, only 9.3% of the total land use is taken up by energy crops and 90.7% of total land use is allocated to renewable electricity resources. Despite this, land use by energy crops in the compromise solution is zero.

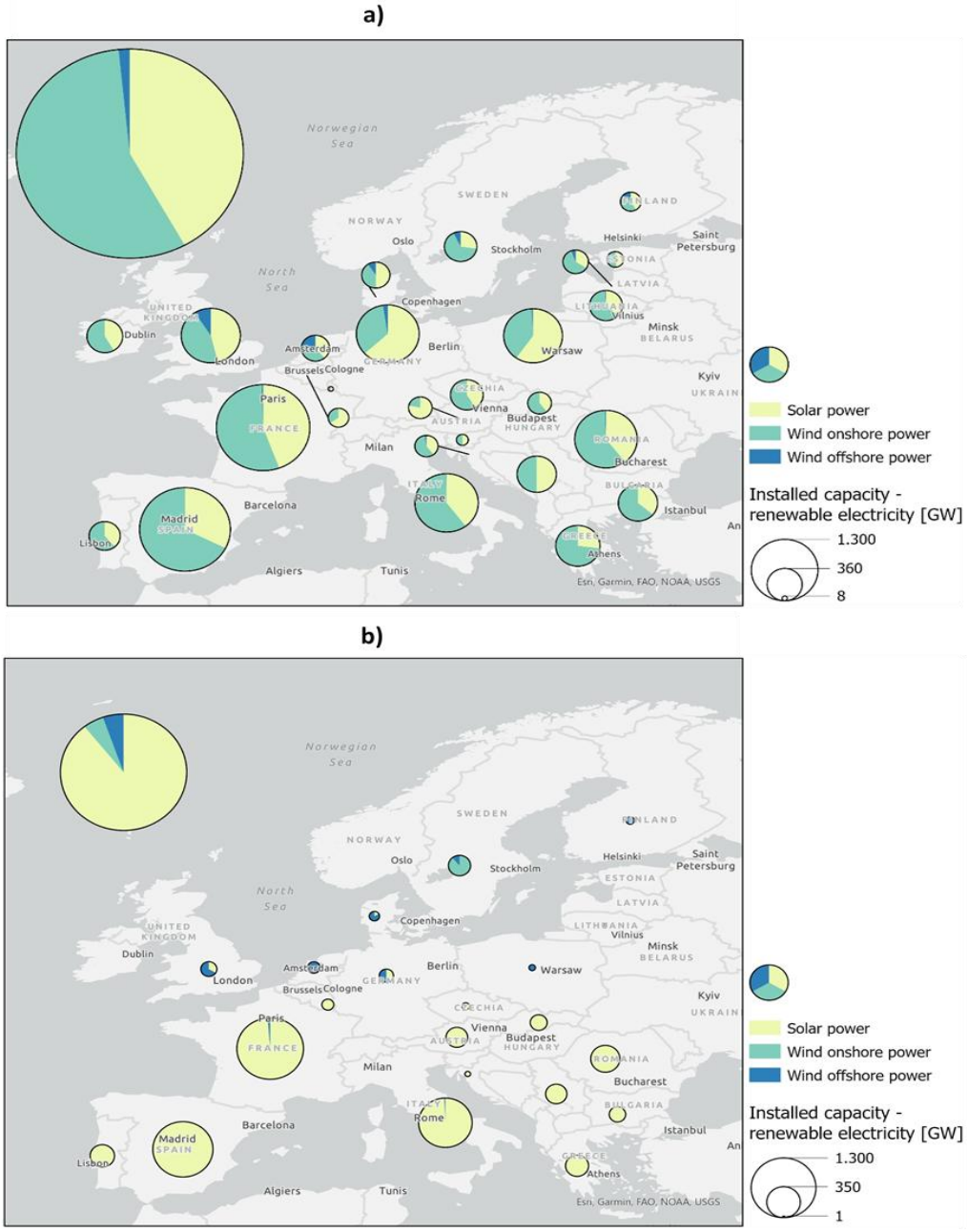


Figure 6-7: Share of land used and installed capacity of renewable electricity a) in cost-optimal solution, b) in compromise solution

Figure 6-8 illustrates the share of each production pathway (BtL, PBtL, PtL) in producing fuels in the cost-, land-, and water-optimal solutions respectively over all periods. The size of pie charts shows the amount of fuel produced in each country. The total amount of produced fuel and the overall share of production pathways over all countries are represented by the big pie chart in the top left corner of each figure. In the cost-optimal solution, PBtL accounts for 44.0% of fuel produced, PtL 38.2%, and BtL 17.9%. In the compromise solution, PtL technology accounts for 50.4% of total fuel production, PBtL 38.1%, and BtL 11.5%. Although no

energy crops are used in the compromise solution, other types of biomass are used by BtL and PBtL pathways, which means that agricultural and forest residues are used in these two production pathways rather than energy crops.

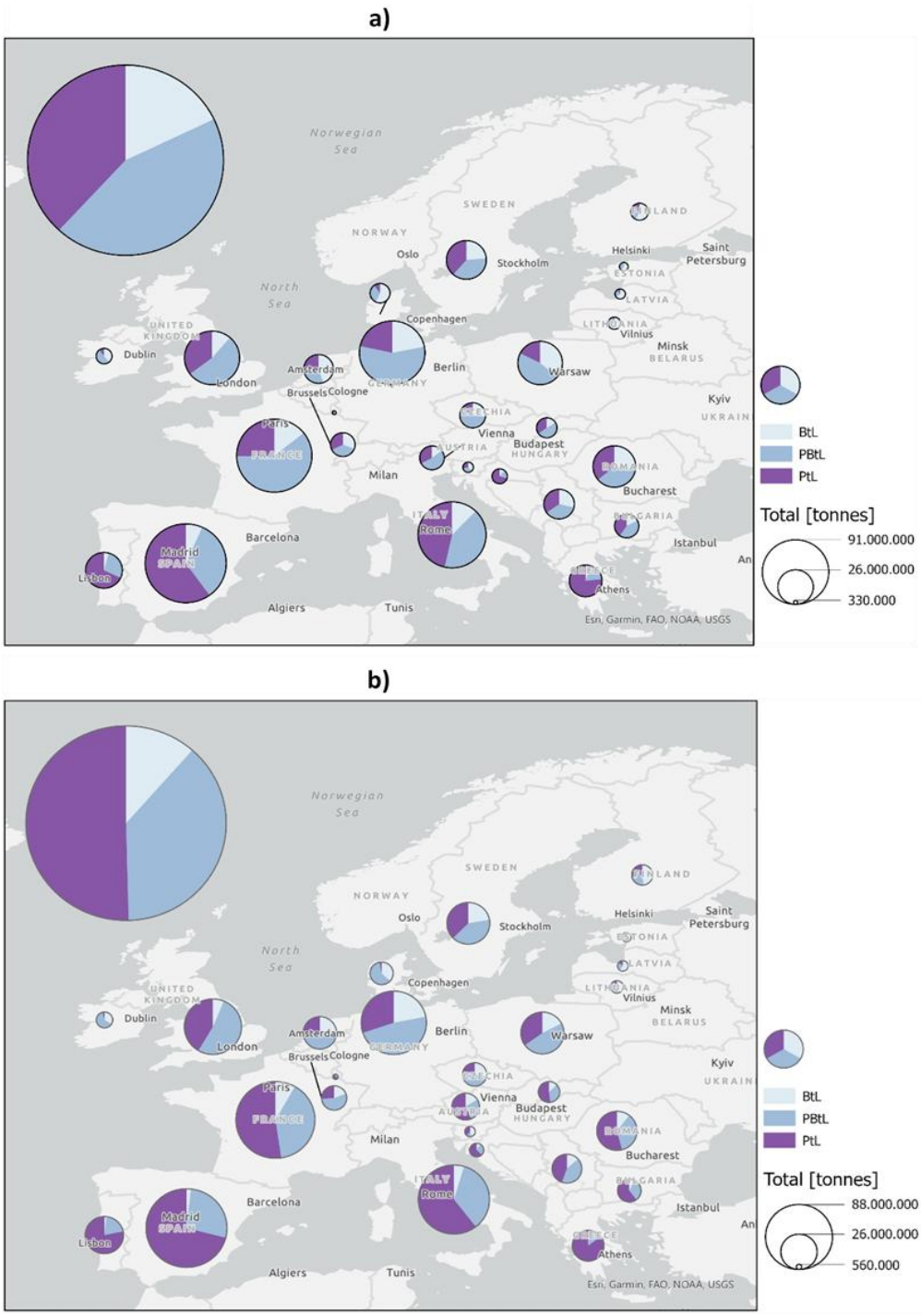


Figure 6-8: Share of each production technology and amount of produced fuels a) in cost-optimal solution, b) in compromise solution

In total, 15.09 TW of renewable electricity is installed over all countries in the cost-optimal solution. In the compromise solution, 4.94 TW of renewable electricity is installed in all countries. Our outcomes show that in the cost-optimal solution, 10.07 TW of solar power capacity, 4.69 TW of wind onshore power capacity, and 0.33 TW of wind offshore power capacity are installed in the last period. These numbers for the compromise solution are 4.58 TW of solar power, 0.24 TW of wind offshore power, and 0.12 TW of wind onshore. France, Spain, and Italy have the highest capacities installed in both solutions compared to other countries, which shows the importance of renewable resources in these countries. In Europe, there were 255 GW of wind capacity installed in 2022. In our study, the compromise solution requires 360 GW of wind capacity to be installed by 2050. Reports indicate that 129 GW of wind capacity will be installed by 2027, a similar magnitude compared to 100 GW of wind capacity required until 2050 by the renewable fuel network of our case study. Furthermore, in 2022, there were 209 GW of solar power installed in Europe. The compromise solution requires 4,580 GW of solar capacity to be installed by 2050. Reports indicate that a total of 484 GW of solar capacity will be installed in the EU by 2026, based on current estimates. According to our results, much more than this needs to be invested in solar power capacity to satisfy the projected demand of renewable fuels in Europe.

In the cost-optimal solution, agricultural residues have the highest share due to their price in the first period, and as they reach their 40% availability limit of use for the transportation sector, the share of energy crops increases to 66%. Results show that water is not a limiting resource. A high proportion of CO_2 sources is used in all solutions, which shows the importance of investing in DAC technology to have access to unlimited CO_2 sources in the future. In the cost-optimal solution, all land available for renewable electricity sources is utilized. However, the compromise solution uses only 2% of available land for wind onshore power in the last period. For offshore wind and solar power, these shares are 46% and 74%, respectively.

6.6 Discussion

In our research, we not only put forward a flexible multi-product, multi-resource, multi-period, and multi-stage model to meet the demand for renewable fuels, but we also took a step further by considering three objective functions in our analysis. By successfully implementing the AUGMECON method and employing the lexicographic method to calculate the range of the right-hand-side of the constrained objective function, we were able to solve a large-scale case study effectively. While previous studies have explored multi-objective optimization in

biofuel supply chains, there has been a gap in the literature when it comes to incorporating three objective functions in a renewable fuel supply chain that encompasses both biomass and renewable electricity sources. Our research fills this void by providing a comprehensive framework that accounts for multiple objectives and considers the integration of various renewable energy sources. We have successfully incorporated land and water use within the SC model. In addition, we actively consider both strategic and tactical decisions to account for the long-term time horizon. This work contributes to advancing the understanding and management of renewable fuel supply chains, facilitating the development of a more sustainable and efficient renewable fuel supply chain.

Based on our results, it is clear that there is a trade-off between the three objective functions. Clearly, no single solution minimizes all objective functions at once. Moreover, the optimal solution for one objective function results in a poor solution for another one. Hence, the consideration of the Pareto-frontier solutions and prioritization based on trade-offs is essential. We find that we could get very close to the optimum value of land use and water use for only a 10% increase in the cost objective function. As a result of the difference between the cost-optimal and compromise solution, it becomes evident that by installing less land-consuming renewable electricity sources and investing in production, storage, and transportation facilities, water and land use can be drastically reduced while maintaining an acceptable level of cost increase. It can be concluded from the results of the case study that water and land are not limiting factors for achieving a cost-efficient solution. It is necessary to invest in storage, transportation, and production facilities in order to ensure that renewable resources are used efficiently.

In this study, it was found that regardless of the criteria used, the amount of imported fuel remained consistent across all solutions. This suggests that meeting the entire 100% demand without imports is challenging based on the current resource potentials and assumptions. Importing fuel is necessary for system stability and viability, raising the need for research on how and from where to import. This result further emphasizes the necessity for a lesser amount of import than what is currently permitted.

The proposed methodology can be utilized for various renewable fuel case studies, encompassing different countries or regions, resources, conversion technologies, and fuel products. However, the application of this approach necessitates the collection of specific data for each case study. The data collection process involves gathering country-level or regional ca-

pacity factors for wind and solar energy, biomass availability, land availability, and water availability. Additionally, it requires acquiring techno-economic parameters for the chosen technologies, such as conversion rates and cost functions for fuel production. Nonetheless, the overall structure of the model and the solution method do not need to be altered. The model can be rerun to explore different scenarios or to update specific case study outcomes when there are significant changes in input parameters. For instance, it can be used with varying assumptions regarding fuel demand, resource prices, or technology performance.

By exploring the domains of trade-offs, expenses, and allocation of resources, we gain a deep comprehension of the intricate dynamics at play. It becomes clear that countries exhibit variations in numerous aspects, leading to diverse results influenced by differing resource availability and contextual factors. Such insights provide valuable information to policymakers, enabling them to grasp the potential impacts of various factors and policy interventions on renewable fuel supply chains. These policies can be customized to suit the specific circumstances of each country, considering the diverse availability of resources and distinct situations. Furthermore, merely focusing on individual objectives is inadequate as it may result in the overlooking of acceptable compromise solutions between economic and environmental goals. Policymakers could encourage the advancement and commercialization of technology in a manner that favors these compromises.

The results indicate that solar power should be prioritized over wind power when considering land use criteria for electricity sources. In terms of renewable fuel technologies, Power-to-Liquid (PtL) is favored over Biomass-to-Liquid (BtL). Nevertheless, biomass can still play a valuable role in reaching an economic solution. Hence, policymakers might consider granting permission for the use of biomass as an initial alternative to produce transportation fuel, as an initiation during the early stages of the transition. To meet the demand for transportation fuels, it may be necessary to permit imports through government-to-government agreements, to ensure feasibility, stability, and energy security. It is crucial to recognize that the utilization of land and water can vary significantly depending on the prioritized criteria within the scope of their availability. It has been noted that while water usage may not be a significant concern when considered on a large scale, local water stress can still exist within the system and must be considered. By leveraging the insights and knowledge gained from these analyses, policymakers can formulate and implement sustainable renewable fuel and energy policies that enhance competitiveness and lay the foundation for a prosperous future. Policymakers can strate-

gically employ this information to facilitate the establishment of a robust infrastructure that supports the growth of renewable fuels. Moreover, they can encourage investments in renewable fuel and energy infrastructure, technology upgrades, as well as research and development initiatives.

Our study has limitations due to potential data inaccuracies, uncertain future parameter manifestations, and limitations of the chosen solution method. To ensure data accuracy, we compared various sources and selected parameter values that represent current expectations for future developments. However, parameters like power densities, the water footprint of energy crops, and resource potentials rely on assumptions, which in some cases lead to contradictions and wide-ranging values in the literature. Different values in power density for example arise from geographical differences, definitional variations, and technological advances. Additionally, using country-level data may overlook localized water scarcity issues.

Considering the 40-year time horizon, uncertainties arise regarding the future development of parameters. It is impossible to predict energy and transportation policies, technology advancements, and market dynamics with certainty. Parameters like resource prices, potentials, technical parameters, and fuel demand are among the uncertain parameters. Uncertainty in demand for example arises from uncertain future developments influenced by government policies, technological advancements, infrastructure development, and changing user preferences.

Our choice of a multi-objective approach with AUGMECON as the solution method balances the advantages of presenting a Pareto front against the disadvantages of limited computational resources and increased complexity in decision-making. Communicating a Pareto front with three objective functions may be challenging for decision-makers.

Supply chain optimization models heavily rely on available data, which can be a drawback due to limited data accuracy and uncertainty about future parameter manifestations. Obtaining accurate and timely data from various sources presents a challenge in optimizing supply chains. Furthermore, the dynamic nature of supply chains is often overlooked, as optimization models typically assume a static environment, failing to account for the evolving reality. In this study, demand emerges as the most sensitive parameter due to factors such as the long time horizon, multiple time periods, and evolving demand based on uncertain factors in the future. It directly affects the configuration of the supply chain, including infrastructure installation and associated costs. Alongside demand, the purchase prices of resources and technology parame-

ters also impact system costs. Additionally, parameters like power density and water usage play a role in meeting environmental criteria.

6.7 Conclusion

Our study presents a multi-objective decision-making framework that stakeholders (policymakers, investors, producers, etc.) can use to determine the most appropriate trade-off decisions based on their priorities. Our paper studies a multi-period, long-term, multi-product, and multi-feedstock supply chain network of renewable fuels targeted at the transportation sector. A mathematical model is proposed for designing an optimal supply chain that minimizes the cost, the land used for renewable resources, the water used for H_2 production, and the water used for biomass cultivation. This work utilizes the augmented ε-constraint method to solve the proposed model to obtain strongly efficient Pareto optimal sets. A case study for the EU+UK countries is presented to demonstrate the effectiveness of the proposed model and gain insight into a future infrastructure system.

The results also show that no single solution simultaneously minimizes all three performance criteria. In this regard, it is crucial to consider Pareto-frontier solutions and prioritize based on trade-offs. We find that we could achieve a nearly optimal value of land use and water use by increasing total cost by only 10%. There is evidence that renewable fuels do not stress water resources in our case study. How much stress there is on land resources, however, depends on the prioritization criteria: It might be a critical resource in cost-optimal solutions or not a major concern in compromise solutions. Results show that in none of the economic and environmental solutions, the pre-dominant production pathway is BtL indicating that renewable electricity and CO_2 as carbon sources are required. Biomass as a renewable energy source has limitations due to scarcity, environmental impact, and competing resource usage. According to the findings, renewable electricity sources need to be prioritized for development and investment. In line with current installations of solar and wind power in the EU and estimates of future installations, the amount of wind power required for the compromise solution of our case study can probably be achieved realistically. Solar power, however, requires a much greater investment in additional installed capacity. The amount of imported fuel is almost uniform across all solutions and objectives, which implies that import is crucial to achieving a feasible solution. A stable supply chain thus may require more research and investment in the import option. It is crucial to invest in storage and transportation facilities to maintain efficient utilization of the resources. Infrastructure installation will also be critical, but can also create major

new industries and opportunities for commercial growth and employment. Despite some unique characteristics of the case study presented in his paper, the general principles and competing nature of different objective functions (economic, environmental) resulting from the interplay of the available resources and technologies can be expected to apply to other cases of renewable fuel supply networks as well.

In this study, it was found that regardless of the criteria used, the amount of imported fuel remained consistent across all solutions. This suggests that meeting the entire 100% demand internally is challenging based on the current potential and assumptions. Importing fuel is necessary for system stability and viability, raising the need for research on how and where to import. This result also highlights the opportunity to analyze the impact of different import scenarios and explore the trade-off between imports and land/water usage.

In future research, social objectives should be considered for a sustainability analysis of this system. We also recommend investigating the land use effects of production, storage and transportation facilities for large-scale renewable fuel production networks. The simultaneous impacts of land use and competition for resources on the supply chain performances and decisions could be studied. Another vital step would be to consider uncertainties in such a dynamic environment.

6.8 Acknowledgement

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6.9 Appendix: Input data

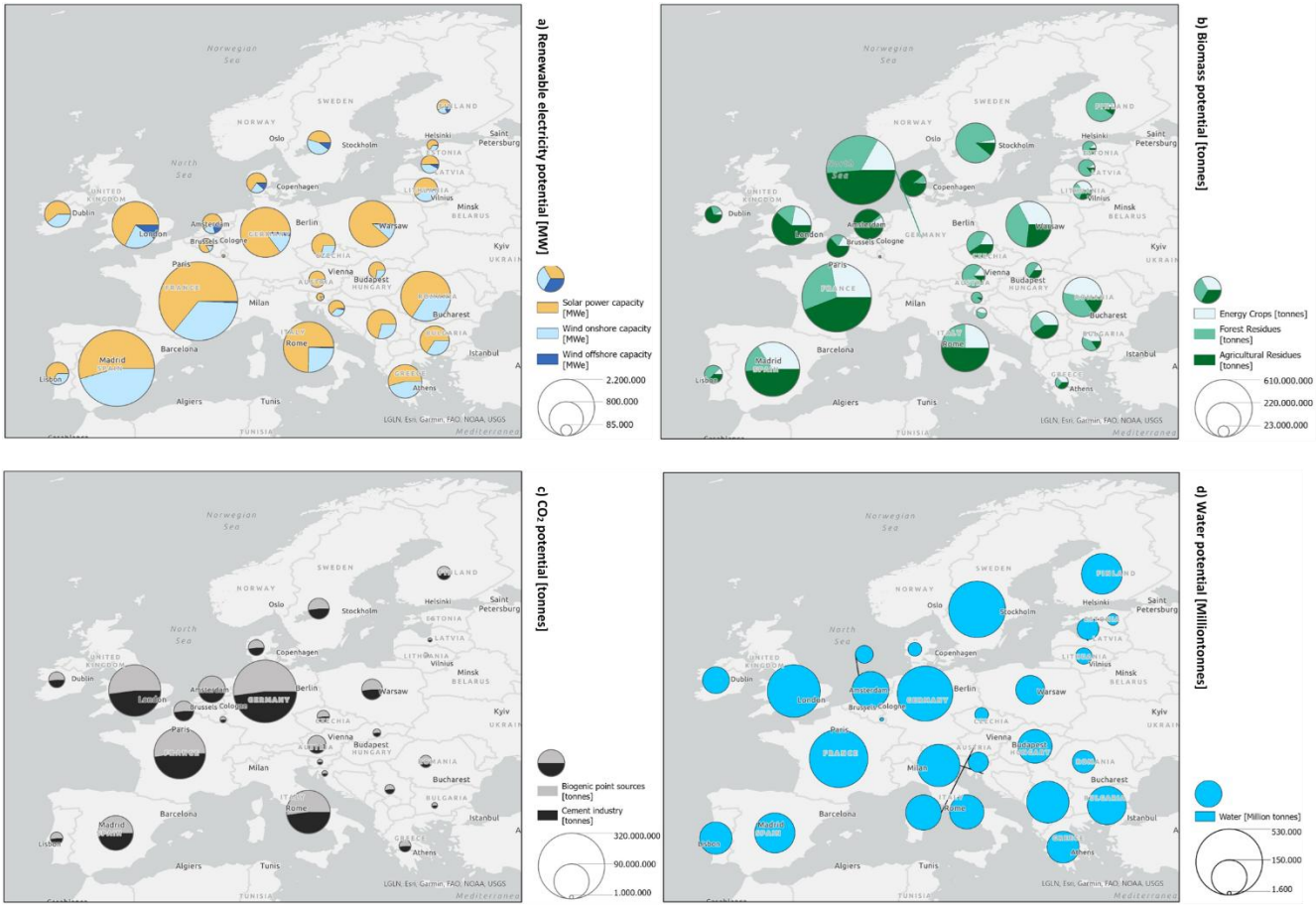


Figure A 6-1: Potential of resources in EU countries

a) Renewable electricity potential b) Biomass potential c) CO_2 potential d) Water potential based on (European Commission Joint Research Centre, 2019a, 2019b, 2019c; Eurostat, 2022; Siegemund, Trommler, Zinnecker, et al., 2017)

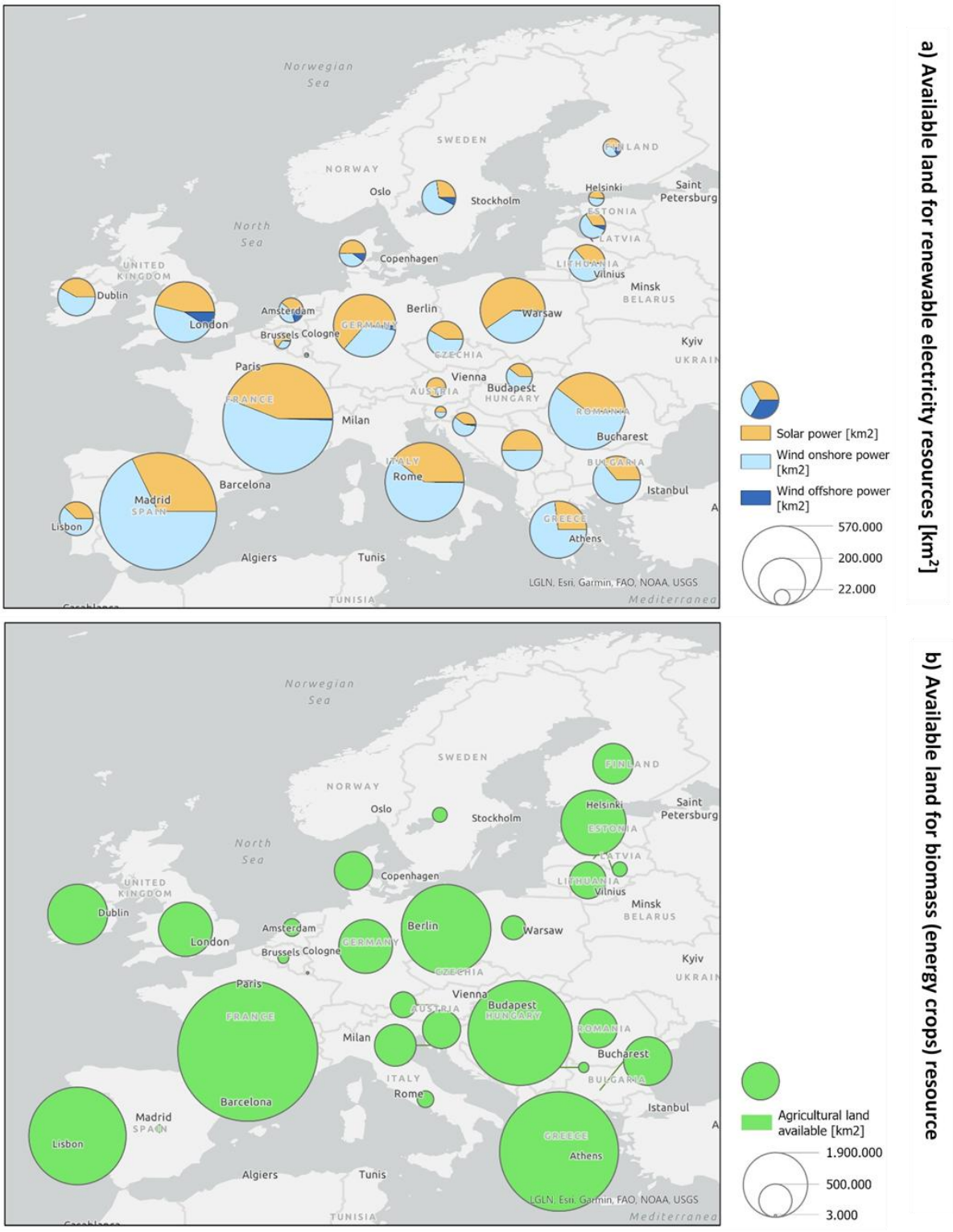


Figure A 6-2:Available land for different renewable resources in each EU country a) Renewable electricity b) Energy crops based on (European Commission Joint Research Centre, 2019a, 2019b, 2019c; Ruiz et al., 2019)

Table A 6-1: Techno-economic data of production technologies based on (FVV, 2021; Liebich et al., 2021)

Techno-logy	Pro-duct	Capacity per plant [tonne/hour]	Period available	Investment cost [€/plant]	Operation & Maintenance cost [€/year/plant]
BtL	FT-fuels	8.08	T1	535,574,070	4% of Investment cost
		44.29	T2	2,251,254,770	
		116.71	T4	3,947,078,583	
PtL	FT-fuels	8.08	T1	366,702,289	4% of Investment cost
		44.29	T2	1,541,411,959	
		116.71	T4	2,702,525,815	
PtL_DAC	FT-fuels	8.08	T1	366,702,289	4% of Investment cost
		44.29	T2	1,541,411,959	
		116.71	T4	2,702,525,815	
PBtL	FT-fuels	8.08	T1	488,069,580	4% of Investment cost
		44.29	T2	2,051,572,382	
		116.71	T4	3,596,979,569	
BtL	MeOH	16.70	T1	403,570,462	4% of Investment cost
		72.98	T2	1,477,552,894	
		185.57	T4	3,440,674,106	
PtL	MeOH	16.70	T1	399,920,450	4% of Investment cost
		72.98	T2	1,464,189,464	
		185.57	T4	3,409,555,621	
PtL_DAC	MeOH	16.70	T1	399,920,450	4% of Investment cost
		72.98	T2	1,464,189,464	
		185.57	T4	3,409,555,621	
PBtL	MeOH	16.70	T1	364,545,689	4% of Investment cost
		72.98	T2	1,334,675,325	
		185.57	T4	3,107,965,102	
DAC	CO_2	0.23	T1	365,400	4% of Investment cost
PEM electroly-sis	H_2	0.30	T1	1,160,000	2% of Investment cost
		7.51	T1	165,750,000	
		30.03	T1	414,000,000	
AEL electroly-sis	H_2	0.30	T1	7,000,000	2% of Investment cost
		7.51	T1	155,250,000	
		30.03	T1	497,000,000	

Table A 6-2: Material and energy inputs of production technologies based on (Liebich et al., 2021)

Resource inputs ([tonne/tonne], [MWh/tonne])/ Production technologies	BtL (FT-fuels)	PtL (FT-fuels)	PtL_DAC (FT-fuels)	PBtL (FT-fuels)	BtL (MeOH)	PtL (MeOH)	PtL_DAC (MeOH)	PBtL (MeOH)	DAC	PEM Electrolysis	AEL Electrolysis
Electricity	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.70	-52.83	-49.33
CO_2 point sources	0.00	-3.14	0.00	0.00	0.00	-1.73	0.00	0.00	0.00	0.00	0.00
CO_2 from DAC	0.00	0.00	-3.14	0.00	0.00	0.00	-1.73	0.00	1.00	0.00	0.00
Biomass	-7.57	0.00	0.00	-2.00	-2.90	0.00	0.00	-1.02	0.00	0.00	0.00
H_2	0.00	-0.48	-0.48	-0.32	0.00	-0.21	-0.21	-0.12	0.00	1.00	1.00
Water	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-9.27	-9.01
FT-fuels	1.00	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
MeOH	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00	0.00	0.00	0.00

Table A 6-3: Transportation data based on (Fasihi et al., 2019; Leduc, 2009; McCollum & Ogden, 2006; Reuß et al., 2017; Wang et al., 2020; Wolter, 2021)

	Capacity [tonne/hour]	Investment cost [€/km]	O&M cost [€/km/year]	Variable cost [€/tonne]	Variable distance related [€/tonne/km]
Fuel truck	-	-	-	1.9	0.07
CO_2 pipeline	83.3 833.3	334,741 941,111	2% of Investment cost	6.8 9.8	-
CO_2 truck	-	-	-	3.8	0.14
H_2 pipeline	390.4 141.1 36.04	3,420,000 2,520,000 1,590,000	4% of Investment cost	-	-
H_2 truck	-	-	-	446.3	4.9
Biomass truck	-	-	-	14.6	0.02
MeOH truck	-	-	-	2.8	0.06

Table A 6-4: Storage data based on (Akhtari et al., 2018; FVV, 2021; Reuß et al., 2017)

	Capacity [tonne]	Investment cost [€]	O&M cost [€/year]
Fuel storage	77,000	70,789,000	2% of Investment cost
H_2 storage	3,984	81,000,000	2% of Investment cost
Biomass storage	20,729	764,078	5% of Investment cost
CO_2 storage	20,729	11,115,930	5% of Investment cost

Table A 6-5: Country-specific surface power density based on (European Commission Joint Research Centre, 2019b, 2019c)

Country\ Power density	Solar power [MW/km^2]	Wind onshore power [MW/km^2]	Wind offshore power [MW/km^2]
Austria	5.9	2.2	-
Belgium	6.9	2.4	5.0
Bulgaria	5.4	1.6	5.0
Croatia	5.7	2.1	5.0
Cyprus	5.8	1.7	-
Czech Republic	5.6	2.5	5.0
Denmark	5.4	2.5	5.0
Estonia	6.3	2.5	5.0
Finland	5.6	2.5	5.0
France	6.3	1.7	5.0
Germany	5.5	1.7	-
Greece	5.5	2.3	-
Hungary	5.4	2.5	-
Ireland	6.0	1.3	5.0
Italy	5.4	2.5	5.0
Latvia	5.3	2.1	5.0
Lithuania	6.5	1.6	-
Luxembourg	7.2	2.5	5.0
Malta	5.7	1.0	5.0
Netherlands	5.8	2.0	5.0
Poland	5.4	1.8	5.0
Portugal	5.7	1.4	-
Romania	5.9	1.1	-
Slovakia	5.5	2.2	5.0
Slovenia	6.1	2.5	5.0
Spain	6.5	2.2	5.0
Sweden	5.9	2.2	-
United Kingdom	6.9	2.4	5.0

Table A 6-6: Fuel demand based on (Alvarado, 2016; IRENA AND METHANOL INSTITUTE, 2021; Siegemund et al., 2017; Wang et al., 2020)

Fuel demand [tonne]\Period	2020-2030 (T1)	2031-2040 (T2)	2041-2050 (T3)	2051-2060 (T4)
FT-fuel	52,750,000	116,386,367	269,159,091	340,704,545
H_2	1,336,336	2,672,673	9,129,129	17,297,297
MeOH	33,320,000	40,800,000	105,400,000	170,000,000

Table A 6-7: Price of import based on (FVV, 2021)

Fuel price [€/tonne]\Period	1	2	3	4
FT-fuel	4,495	3,966	3,438	2,910
H_2	2,367	2,091	1,816	1,540
MeOH	6,333	5,666	5,000	4,333

Table A 6-8: Price of CO_2 based on (Brynolf et al., 2018)

Price [€/tonne]\Period	T1	T2	T3	T4
Cement industry	70	60	40	30
Biogenic point sources	20	20	20	20

Table A 6-9: Price of biomass, water and renewable electricity based on (European Commission Joint Research Centre, 2019a; Searle & Christensen, 2018; Varone & Ferrari, 2015)

Country	Average price of energy crops [€/tonne]	Average price of agricultural residues [€/tonne]	Average price of forest residues [€/tonne]	Average price of water [€/tonne]	Average electricity price from solar power [€/MWh]	Average electricity price from wind power [€/MWh]
Austria	76.6	7.1	9.9	3.7	54.0	90.6
Belgium	67.3	2.0	6.5	4.6	70.5	202.9
Bulgaria	78.0	5.9	7.2	1.1	44.5	142.6
Croatia	176.9	3.4	20.4	2.0	59.0	135.7
Czech Republic	65.9	3.5	10.4	3.5	66.6	182.2
Denmark	227.7	20.5	14.3	9.5	77.3	86.1
Estonia	169.4	6.8	45.9	3.4	118.4	109.7
Finland	42.9	1.3	20.5	6.0	182.5	95.7
France	81.9	0.5	3.7	4.1	53.5	115.3
Germany	157.0	2.8	2.3	2.0	80.2	108.3
Greece	5.6	4.7	6.0	1.3	38.7	118.4
Hungary	25.9	6.5	5.6	2.2	45.5	108.3
Ireland	86.7	1.0	42.0	3.4	91.1	135.7
Italy	32.0	30.0	4.0	2.0	47.9	79.9
Latvia	148.6	21.8	42.8	3.4	115.0	155.3
Lithuania	95.2	0.9	46.5	3.4	123.0	149.4
Luxembourg	19.3	0.0	3.3	5.6	79.5	108.1
Netherlands	44.3	1.8	104.5	5.6	245.2	93.9
Poland	42.3	3.2	6.8	2.8	81.1	95.2
Portugal	21.3	3.1	3.0	1.9	29.4	100.8
Romania	22.0	6.6	19.1	1.4	45.0	123.1
Slovakia	73.5	7.5	4.7	2.5	54.0	150.0
Slovenia	49.9	0.9	10.2	2.3	71.3	88.1
Spain	34.6	3.8	22.0	1.9	36.4	97.6
Sweden	64.1	1.1	5.5	4.5	131.7	35.4
United Kingdom	88.8	0.0	13.0	3.6	82.0	131.8

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Chapter 7

7 EU-wide renewable fuel supply chain design under variable renewable electricity: A two-stage stochastic programming approach

Authors: Mina Farajiamiri, Jörn-Christian Meyer, Grit Walther

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Keywords: Two-Stage Stochastic Programming, Renewable Fuel, Renewable Variability, Supply Chain Network Design, Mixed Integer Linear Programming

Abstract

Decarbonizing hard-to-electrify sectors such as heavy-duty transport, aviation, and shipping requires renewable fuels, including Fischer–Tropsch fuels, methanol, hydrogen, and ammonia. Their large-scale deployment depends on supply chains that can coordinate diverse feedstocks and pathways while remaining resilient to fluctuations in renewable electricity. Most existing models assume deterministic electricity availability, overlooking the variability of wind and solar generation that strongly affects renewable fuel pathways, system costs, and infrastructure decisions.

To address this gap, we develop a two-stage stochastic mixed-integer linear programming framework that integrates renewable electricity uncertainty into multi-fuel supply chain optimization. The model links strategic infrastructure investments with tactical operational decisions, embedding both contract and spot imports as complementary hedging options. Probability distributions derived from thirty years of wind and solar data generate a scenario set that captures seasonal variability across a multi-period horizon.

The framework contributes methodologically by embedding renewable intermittency and dual import mechanisms into a large-scale stochastic supply chain network design model. Empirically, an EU-wide case study with 81 scenarios demonstrates how variability and import strategies jointly shape infrastructure development. Results show that deterministic designs systematically underestimate costs and misallocate capacity, while the stochastic approach produces robust, cost-efficient configurations. The analysis highlights trade-offs across fuels, be-

tween domestic expansion and reliance on imports, offering both methodological advances in stochastic supply chain design and policy-relevant insights for resilient, climate-aligned fuel systems.

7.1 Introduction

Decarbonizing heavy-duty transport, aviation, and shipping requires renewable fuels that can complement or substitute fossil-based energy carriers where direct electrification is infeasible (IEA, 2022). Renewable "drop-in" fuels, such as methanol (MeOH), and Fischer-Tropsch fuels (FT-fuels), can replace fossil fuels in existing vehicles and distribution systems without requiring new infrastructure (Olah, 2005; Siegemund et al., 2017). Hydrogen (H_2) is also gaining recognition as a key energy carrier and intermediate, and its production is expected to increase significantly (Abdin et al., 2020). Green ammonia (NH_3) is another promising fuel with potential advantages, despite challenges related to toxicity and infrastructure adaptation (DNV GL - Maritime, 2019; Xing et al., 2021).

Scaling renewable fuels requires supply chains (SC) that integrate multiple feedstocks and carriers, balance domestic and imported resources, and rely on advanced modeling to capture technological diversity, seasonal dynamics, and long-term demand (Wolff et al., 2023). When powered by renewable electricity, these fuels can reduce emissions, enhance energy security, and enable long-term storage. Yet planning must also account for resource availability, logistics, and global trade. In regions such as the EU, characterized by high demand but limited renewable potential, imports will remain essential for meeting long-term fuel needs (Giannelos et al., 2021; Vos et al., 2020; Nichol et al., 2023). Within this context, imports play a dual role as both a resource and a hedge against uncertainty. Two types are particularly relevant: contract imports, secured through long-term agreements that provide stable volumes and predictable prices but limited flexibility, and spot imports, procured on short notice at higher costs to address unforeseen shortfalls. Capturing both mechanisms is critical, as contract imports enhance security of supply while spot imports offer flexibility to absorb shocks. Yet, despite their practical importance, differentiated import strategies remain largely absent from renewable fuel supply chain network design models. These diverse factors are therefore critical for robust and sustainable SC outcomes.

A central challenge is that these fuels rely on renewable electricity for production, and renewable generation is inherently intermittent. Solar photovoltaics (PV) and wind turbines, the fastest-growing renewable sources, exhibit strong temporal and spatial variability (Fattahi & Govindan, 2018; Huang et al., 2014; Quddus et al., 2018). Mismatches between renewable supply and power demand can cause curtailments, wasting valuable energy, or shortages when demand exceeds supply. Although the variability of renewable energy sources (RES) is well

documented in the power systems literature, supply chain network design (SCND) models typically assume deterministic inputs or rely on average capacity factors (Carreras et al., 2021; Demirhan et al., 2020; Denholm et al., 2013). Such simplifications overlook seasonal and interannual variability that critically affect production scheduling, storage utilization, and long-term infrastructure investments. As a result, they risk underestimating costs, overinvesting in rigid assets, and designing supply chains that are unable to adapt to real-world fluctuations. In contrast, explicitly capturing renewable variability can reveal different infrastructure priorities, trade-offs between domestic and imported resources, and the robustness of long-term fuel strategies.

It should be mentioned that deterministic planning approaches risk generating designs that may be economically suboptimal or operationally infeasible when actual conditions deviate from forecasts (Aghezzaf et al., 2010; Bertsimas et al., 2013). Increasingly, renewable fuel SC models take uncertainties into account when making decisions, typically through stochastic programming (Azadeh et al., 2014; Cobuloglu & Büyüktahtakın, 2017; Nur et al., 2021; Tong, Gong, et al., 2014; Xie & Huang, 2018; You, 2013), or robust optimization (Bairamzadeh et al., 2018; Delkhosh & Sadjadi, 2020; Gilani & Sahebi, 2020; Huang et al., 2025; Liu et al., 2022). Robust optimization avoids reliance on detailed probabilistic information and provides solutions resilient to worst-case scenarios; however, it often yields overly conservative network configurations (Gorissen et al., 2015). Stochastic programming, on the other hand, effectively utilizes probabilistic information to optimize decisions under uncertainty, albeit with higher data requirements and computational complexity (Birge & Louveaux, 2011). Despite their respective advantages and disadvantages, stochastic programming is favored here for its ability to deliver more realistic and economically balanced solutions that adequately capture the complex uncertainty dynamics inherent in renewable fuel SC design.

Against this backdrop, the aim of this work is to design flexible SCs that remain resilient under variable RES availability, thereby enabling efficient renewable fuel production across diverse geographical contexts. To this end, we develop a two-stage stochastic mixed-integer linear programming framework that integrates RES variability and dual import mechanisms into SC design. In the first stage, strategic investments are made prior to the realization of uncertainty; in the second stage, operational recourse decisions adjust first-stage decisions in response to scenario realizations. Uncertainty is represented through probability distributions of wind and solar capacity factors derived from 30 years of historical data, enabling the construc-

tion of a realistic scenario set. The objective is to minimize expected system costs while ensuring resilience to RES fluctuations. Using an EU case study, this research addresses two guiding questions. 1) What is the expected total cost of a renewable fuel SC under uncertain conditions? 2) What is the best SC configuration that responds to varying scenarios? Answering these questions will highlight how resource intermittency and uncertainty influence SC design and offer strategic insights for developing robust, future-ready energy infrastructures.

The main contributions of this study are:

- Developing a flexible large-scale stochastic MILP optimization model that integrates multiple fuels, feedstocks, and pathways, captures seasonal variability over a multi-period horizon, and embeds both contract and spot import options.
- Explicitly modeling uncertainty in renewable electricity supply within the renewable fuel supply chain design.
- Demonstrating the approach in a European-wide case study with 81 scenarios, highlighting how renewable intermittency and differentiated import strategies jointly influence infrastructure investment and system performance.

The organization of this paper is as follows: Section 2 presents a review of the existing literature, research gaps, and the contribution of this work. The problem's specific characteristics, context, and methodology are explained in Section 3. Section 4 describes a case study and scenario design. Section 5 presents results and discusses them. Finally, section 6 provides conclusions and directions for future research.

7.2 Literature review

This literature review specifically targets renewable fuel SC design, emphasizing the distinct characteristics of such networks, sources of variability and uncertainty, particularly via stochastic programming, and identifying critical limitations in current approaches.

7.2.1 Supply chain design

A significant body of literature has explored SC optimization through mathematical models capable of capturing network complexity, diverse planning horizons, inventory management, and intricate production processes (Melo et al., 2009). While general multi-commodity models exist (Melo et al., 2009), research often targets specific resources like fossil or biomass-based fuel SCs (De Meyer et al., 2014). Renewable fuel research has predominantly concentrated on single-resource systems, particularly biofuel and H_2 SCs (Ghaderi et al., 2016; Zandi

Atashbar et al., 2018). Yet, few studies integrate multiple renewable resources or technologies into flexible renewable fuel SCs, even though relying on a single fuel risks rigid, less resilient systems and overlooks synergies essential for robust, cost-effective decarbonization (Farajiamiri et al., 2023; Wolff et al., 2023; Zardoshti Zadeh Yazdi & Walther, 2025), representing an important gap in the literature.

A multi-period framework is essential to capture dynamic investments and capacity expansions, which single-period models cannot adequately represent (Almansoori & Shah, 2009). Besides, existing research often targets a single region or relatively short planning horizons, limiting the generalizability and scalability of the findings (Govindan et al., 2017). Although these localized analyses are valuable, the global shift toward cleaner energy systems necessitates an understanding of large-scale, multi-country networks.

Given the capital-intensive and largely irreversible nature of strategic SC decisions, such as facility location and technology selection (Huang et al., 2014; Melo et al., 2009) it is essential to account for uncertainty in order to avoid lock-in and misallocation. Accordingly, SC design under uncertainty has become a prominent research area. Various approaches have been employed to balance profitability and operational responsiveness, including recourse-based (Santoso et al., 2005) and risk-averse stochastic programming, robust optimization (Pishvaee et al., 2011), fuzzy mathematical programming (Ji et al., 2007), and scenario-based (Azaron et al., 2020) and decomposition methods (Schütz et al., 2009). However, most contributions remain generic or applied to conventional supply chains. More empirical work is needed to identify which uncertainties are most critical in specific energy and industrial contexts and how decision-making strategies under uncertainty affect system performance (Simangunsong et al., 2012).

7.2.2 Renewable fuel supply chain under uncertainty

Within renewable fuels, research has primarily focused on biofuels, with models addressing uncertainties in biomass supply, feedstock characteristics, yields, and transport logistics (Aboytes-Ojeda, Castillo-Villar, & Eksioglu, 2022). Two-stage stochastic programming (TSSP) has been widely used, where first-stage strategic choices (locations, capacities) are followed by second-stage recourse actions (production, logistics) once uncertainties are realized (Birge & Louveaux, 2011). Although these approaches have yielded cost-effective solutions and more robust designs, they generally focus on single-resource, biomass-centric models re-

stricted to localized or single-country settings. Consequently, the findings from these studies have limited applicability as global SCs move toward diversified renewable energy portfolios.

In contrast, studies of hydrogen (H_2) supply chains are fewer but growing. Early works provided deterministic baselines (Almansoori & Shah, 2009; Reuß et al., 2017), while later studies increasingly applied scenario-based stochastic programming (Almansoori & Shah, 2012; Dayhim et al., 2014; Nunes et al., 2015) to capture demand variability. Recent contributions extend this by integrating data-driven robust optimization (Zhou et al., 2024) and a TSSP model with multiple uncertainty sources (Efthymiadou et al., 2025) to address broader uncertainties in demand, prices, and supply. While these contributions highlight the value of modeling uncertainty for more resilient H_2 infrastructure design, they are generally restricted to single-carrier systems and national or regional settings. A comprehensive supply chain perspective that simultaneously integrates H_2 with other fuels and energy carriers under uncertainty is still largely missing, leaving a gap in understanding how diversified renewable portfolios can be jointly optimized.

Table 7-1 provides a comprehensive overview of these studies.

Table 7-1: Overview of related works

Ref	Multiple resources	Multiple storage	Multiple transportation	Products	Planning periods	Model specification	Uncertainty method	Uncertaint parameter	Uncertainty in resource availability	Seasonality	Case study
(Wolff et al., 2023)	✓		✓	FT-fuels	Multi-period	MILP	Deterministic			✓	EU+UK
(Vo et al., 2025)	✓	✓		MeOH	Multi-period	MINLP	Deterministic				
(Reuß et al., 2017)	✓	✓	✓	H_2	Multi-period	MILP	Deterministic			✓	EU
(Almansoori & Shah, 2012)	✓	✓		H_2	Multi-period	MILP	SP	Demand		✓	UK
(Nunes et al., 2015)				H_2	Multi-period	MILP	SP	Demand		✓	UK
(Dayhim et al., 2014)	✓			H_2	Multi-period	MILP	SP	Demand			New Jersey
(Efthymiadou et al., 2025)	✓			H_2	Multi-period	MILP	SP	Demand, biomass availability, gas price, technology costs	✓	✓	UK
(Kim et al., 2008)		✓	✓	H_2	Single-period	MILP	SP	Demand			Korea
(Kim et al., 2024)				H_2	–	MINLP	SP	Renewable energy sources, demand	✓	✓	trades in 9

										regi-ons
(Aboytes-Ojeda et al., 2019)			Biofuel	Single-pe-riod	MILP	SP	Biomass supply, moisture, ash con-tents	✓	✓	Texas
(O'Neill et al., 2022)			Biofuel	Multi-pe-riod	MILP	SP	Biomass yield		✓	Michi-gan
(Kalhor et al., 2022)	✓		Biofuel	Multi-pe-riod	MILP	Robust	Demand			Iran
(Guo et al., 2022)			Biofuel	Multi-pe-riod	MILP	SP	Biomass supply	✓	✓	Il-linois
(Aboytes-Ojeda et al., 2022)			Biofuel	Single-pe-riod	MILP	SP	Biomass quality, bi-omass yield		✓	Texas
(Nur et al., 2021)		✓	Biofuel	Multi-pe-riod	MILP	SP	Biomass quality		✓	South Cent-ral US
(Memişoğl u & Üster, 2021)			Biofuel	Multi-pe-riod	MILP	SP	Biomass yield		✓	Texas
(Sharma et al., 2019)			Biofuel	Single-pe-riod	MILP	SP	Biomass yield		✓	Ten-nessee
(Ghelichi et al., 2018)	✓		Biofuel	Multi-pe-riod	MILP	SP	Feedstock supply, demand	✓	✓	Iran
(Quddus et al., 2018)			Biofuel	Multi-pe-riod	MILP	Chance-constrai-ned	Biomass supply	✓	✓	Mis-sis-sippi
(Osmani & Zhang, 2017)	✓	✓	Biofuel	Multi-pe-riod	MILP	SP	Biomass supply, de-mand, final product selling price	✓	✓	Wis-consin
(Castillo-Villar et al., 2017)			Biofuel	Single-pe-riod	MILP	SP	Biomass quality va-riability			Ten-nes-see.
(Zhang & Osmani, 2015)		✓	Biofuel	Single-pe-riod	MILP	SP	Biomass supply, de-mand, sale price	✓	✓	Ala-bama
(Osmani & Zhang, 2014)	✓	✓	Biofuel	Multi-pe-riod	MILP	SP	Biomass supply, purchase price of biomass, bioethanol demand, sale price of bioethanol	✓	✓	4-sta-tes in the US
(Marufuz-zaman et al., 2014)		✓	Biofuel	Single-pe-riod	MILP	SP	Biomass supply, technology	✓		Mis-sis-sippi.
(Huang et al., 2014)		✓	Biofuel	Multi-pe-riod	MILP	SP	Feedstock supply	✓	✓	Cali-fornia
(Azadeh et al., 2014)			Biofuel	Multi-pe-riod	LP	SP	Demand, price			Iran
(Osmani & Zhang, 2013)	✓	✓	Biofuel	Single-pe-riod	MILP	SP	Biomass supply, purchase price of biomass, bioethanol demand, sale price of bioethanol	✓	✓	North Dakot a
(Awudu & Zhang, 2013)			Biofuel	Single-pe-riod	LP	SP	Demand, price			North Dakot a
(You, 2013)		✓	Biofuel	Multi-pe-riod	MILP	SP	Supply, demand	✓		Il-linois.
(Gebreslas-sie et al., 2012)			Biofuel	Multi-pe-riod	MILP	SP	Supply, demand	✓		Il-linois
(Chen & Fan, 2012)		✓	Biofuel	Single-pe-riod	MILP	SP	Feedstock fluctua-tion	✓	✓	Cali-fornia
(Kim et al., 2011)		✓	Biofuel	Single-pe-riod	MILP	SP	Supply amounts, market demands,	✓		South-east

								market prices, processing technologies			ern region of the US
This work	✓	✓	✓	FT-fuels/ H_2/NH_3 /MeOH	Multi-period	MILP	SP	Availability of renewable electricity	✓	✓	EU+UK

7.2.3 Renewable electricity variability

Given renewable electricity's increasing relevance as a resource for renewable fuels and energy carriers, most SC models treat electricity as a fixed exogenous input (Lara et al., 2018) overlooking the inherent variability of wind and solar resources (Kwon, 2010; Quan et al., 2015; Zhang et al., 2020). This inherent intermittency of renewable electricity generation significantly impacts production scheduling, storage strategies, and overall SC design (Dell'Aversano et al., 2024) integration of solar and wind variability and their interactions with fuel production pathways remains notably underexplored. Among the few exceptions is the study by Osmani & Zhang (2014) which explicitly addresses wind power variability within renewable fuel SC models.

In the broader energy literature, probabilistic models based on historical data and Monte Carlo simulations are widely used to capture renewable fluctuations (Li et al., 2024; Lin et al., 2022). and stochastic simulation–optimization frameworks have been developed to evaluate techno-economic performance under uncertainty (Liao et al., 2024; Sakki et al., 2022). Despite these advances, sophisticated modeling and optimization approaches remain limited in the context of renewable fuel SCs, where they are crucial for enhancing system reliability, reducing costs, and ultimately supporting the transition to sustainable energy systems.

Research on power-system planning and operation underscores why ignoring uncertainty in RES is risky. Stochastic generation-expansion studies for Germany and the UK reveal that deterministic planning systematically understates the need for flexible or back-up capacity when wind and solar deviate from forecasts (Kendziorski et al., 2017; Sharifzadeh et al., 2017). Robust and hybrid robust-stochastic formulations go further, hardening investment choices against worst-case shifts in demand, fuel prices, and renewable output (Dehghan et al., 2014, 2016). Joint optimization of generation, storage, and transmission underscores the value of flexibility in smoothing renewable fluctuations (Wang et al., 2023; Yang et al., 2017). On the operational side, stochastic security-constrained unit-commitment models that embed wind- and solar-forecast errors reduce expected dispatch costs and sharpen reserve requirements (Quan et al., 2016). Nevertheless, the economic repercussions of renewable variability extend well be-

yond the power plant. In liberalized markets, uncertainty shifts risk among generators, retailers, and consumers (Yi et al., 2018), while upstream bottlenecks can delay capacity additions and raise costs. Yet renewable fuel supply chain studies often overlook these dynamics, implicitly assuming perfectly available renewable electricity. This creates a critical knowledge gap; we lack insights into how renewable variability propagates through emerging renewable fuel supply chains and shapes investment and operational strategies.

7.2.4 Research gaps and contributions

In summary, current renewable fuel SC optimization research has advanced uncertainty modeling but remains constrained by three major limitations:

1. Limited focus on supply chain components: Most studies simplify one or more dimensions of the system, focusing on a single resource or product, or neglecting diversity in storage options and transportation modes, thus missing synergies essential for resilient decarbonization.
2. Limited scope and short-term horizons: Analyses are often localized and short-term, limiting scalability and relevance to continental or long-term planning contexts.
3. Neglect of electricity variability: Despite its central role in renewable fuel production, wind and solar intermittency are rarely integrated into SC models, leaving a critical gap between power system and supply chain research.

This study addresses these gaps through several contributions. We develop a flexible, large-scale stochastic MILP model that integrates multiple fuels, feedstocks, pathways, storage types, and transportation modes, while also capturing seasonal variability, thereby overcoming the limited focus of previous works. To move beyond localized and short-term models, we propose a long-term, multi-period framework applied at the continental (EU+UK) scale, enabling investment and capacity-expansion planning over time. To address the neglect of renewable electricity variability, we explicitly incorporate variability of wind and solar capacity factors derived from 30 years of historical data into the supply chain design. In addition, we embedded two complementary import strategies, long-term contracts that provide supply security and spot imports that add flexibility, into the optimization framework, a dimension rarely considered in renewable fuel SCND. Together, these contributions move beyond single-product, localized, and deterministic models with simplified trade and infrastructure, offering methodological innovation in stochastic SCND and policy-relevant insights for resilient, cost-efficient

renewable fuel systems. The results show how renewable intermittency reshapes investment, storage, and import strategies, providing a robust analytical blueprint for future energy systems.

7.3 Methodology

In this section, we describe the underlying problem, planning decisions, and how to deal with uncertainty.

7.3.1 Problem statement

Figure 7-1 illustrates the structure of a multi-resource, multi-product renewable fuel SC network based on our case study, yet its structure remains sufficiently generic to be adapted for alternative components and contexts. Our exemplary SC has a wide range of resources, including biomass, water, CO_2 from direct air capture (DAC), CO_2 from cement and biogenic point sources, Nitrogen (N_2) from air separation units (ASU), electricity from wind, and solar power. These feedstocks' availability varies from season to season because of weather conditions and competitive pressures across sectors, which we account for in our model. It is possible to produce FT-fuels and MeOH in three ways: Power-to-Liquid (PtL), Power-Biomass-to-Liquid (PBtL), and Biomass-to-Liquid (BtL). NH_3 can be produced using the Haber–Bosch process. The production of H_2 can be accomplished by electrolysis using the Proton Exchange Membrane (PEM) and Alkaline (AEL) process. Also, each production technology has a different capacity. In this study, we assume that technology infrastructures will continue to be used up to the end of the time horizon and that, as technology matures, investment as well as operation and maintenance (O&M) costs will decrease. Our model assumes that the transportation of biomass, CO_2, H_2, and all fuels by truck is feasible. We also assume that CO_2 and H_2 can be transported via pipelines. It is assumed in our model that there is no existing pipeline infrastructure for CO_2 and H_2 at the beginning of the time horizon. Pipelines carrying CO_2 and H_2 can have different capacities. Also, we consider the storage of CO_2 captured through DAC, H_2, and all fuels as part of our network. We examine two kinds of imports in this paper, namely contracted imports, which are based on long-term contracts, and spot imports, which, due to their significantly higher costs, are chosen by the model only when supply from internal and contracted sources is insufficient. Spot imports, such as purchasing natural gas on the short-term market, are assumed to be much more expensive than contracted imports.

7.3.2 Optimization framework

By using the Resource-Technology-Network (RTN) approach (Samsatli et al., 2015), we can see in Figure 7-1 that our SC network has two types of nodes, circles and rectangles. In our

model structure, all resources ($m \in M$) are represented by circles, including raw materials (biomass, water, CO_2, electricity), intermediates (N_2, H_2), and final products (FT-fuel, MeOH, NH_3). Our model structure also considers the origins of resources ($o \in O$) and a subset of RES including solar and wind power ($r \in RE \subset O$). Technology that transforms resources is represented by a rectangle. Different production pathways ($p \in P$) and modes of transportation ($q \in Q$) are examined in our study. A number of transportation modes ($Q_{inv} \subset Q$) require investments in different pipeline types and capacities. Different storage methods ($l \in L$) are considered for different resources. To reduce the number of periods in long-term planning, we use the time aggregation method (Samsatli et al., 2015). In a time decomposition approach, long-term investment decisions are separated from short-term operational decisions by modeling them on different temporal scales. Accordingly, we consider two planning time levels: strategic time periods ($t \in T$), defined in our case study as decadal (10 years), and tactical time periods ($s \in S$), defined as four seasons per year in our case study. More generally, both the length of the strategic period and the number of seasons per year are parameters that can be adjusted depending on the case study. Each strategic period consists of n annual periods, which are further divided into seasonal periods. A decadal level is derived by aggregating the ($n = 10$) annual periods. Each decade has a representative year that is repeated multiple times. Here, cyclical orders are used to define seasonal time periods, which means that each season's inventory balance is linked to the previous one. There are several regions in the planning area ($i \in I$), each with its own resource potential (R_{oits}) and demand (D_{mits}). Contract and spot imports can also be used to satisfy demand. In this paper, the assumption is that the capacity factors of RES in each region and season are uncertain ($\vartheta_{isr\chi}$) and a discrete set of scenarios ($\chi \in \mathrm{X}$) with associated probabilities ($Pr_\chi,\ \sum_\chi Pr_\chi = 1$) is available.

Improving the reliability of renewable fuel supply chains under uncertainty requires advanced modeling and integrated strategic–tactical planning. Two-stage stochastic programming (TSSP) provides such a framework by linking irreversible “here-and-now” infrastructure decisions with adaptive “wait-and-see” operational decisions. This joint optimization ensures that long-term supply chain designs remain robust and cost-efficient as uncertain conditions unfold.

In TSSP formulations, first-stage decision variables, which are common in all scenarios (here-and-now), represent strategic decisions, and second-stage decision variables, which vary from scenario to scenario (wait-and-see), represent tactical decisions. SC's long-term framework is determined by strategic decisions. 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, on the other hand, operate at a more granular timescale and can be adjusted as uncertainties unfold. In our model, tactical decisions are revisited each season within a given decade. They include allocating resources, setting production rates, managing storage volumes, controlling transportation flows, and procuring feedstocks. Under these assumptions, a two-stage mixed-integer stochastic programming model is formulated, drawing on the deterministic framework of Farajiamiri et al. (2023) while introducing several modifications to account for the present study's requirements. The complete mathematical formulation is presented in the supplementary material.

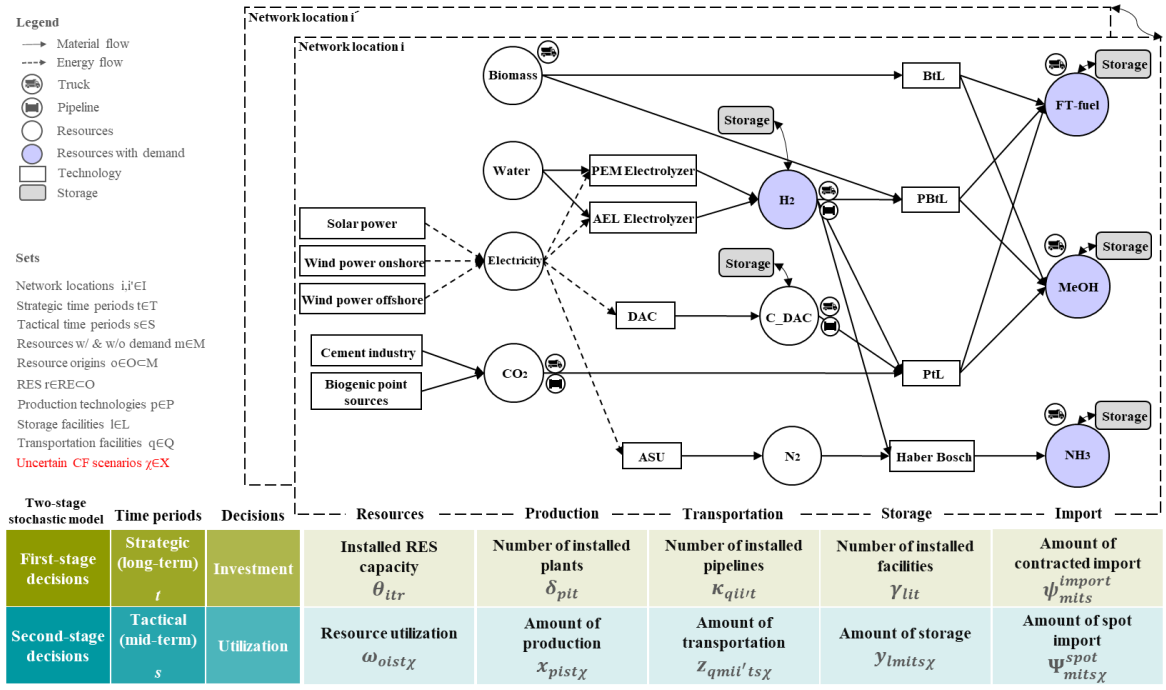


Figure 7-1: Renewable fuel SC with strategic and tactical decisions

The objective function aims to minimize the expected net present value (NPV) of total system costs. It is important to choose a system design so that the discounted costs are minimized across all scenarios and time periods. As TSSP involves two sets of decisions: first-stage (strategic) decisions made before uncertainties are realized, and second-stage (tactical) decisions made after uncertainties are revealed. The total system costs consist of both first and second-stage costs. Equation (7.1) shows the objective functions. First-stage costs, which include investment costs for production ($I_t^{inv,prod}$), storage ($I_t^{inv,stor}$), transportation ($I_t^{inv,trans}$), and RES facilities ($I_t^{inv,RE}$), as well as operation, and maintenance (O&M) costs for these compo-

nents ($I_t^{op,prod}$, $I_t^{op,stor}$, $I_t^{op,trans}$, $I_t^{op,RE}$), and contracted imports (I_t^{import}). Second-stage costs, weighted by scenario probabilities, which comprise variable transportation ($I_{t\chi}^{var,trans}$), resource procurement ($I_{t\chi}^{var,res}$), and spot imports ($I_{t\chi}^{spot}$). The detailed NPV calculations for the individual cost components are provided in the appendix.

$$Min\ ETC = \sum_{t\in T} I_t^{inv,prod} + I_t^{inv,stor} + I_t^{inv,trans} + I_t^{inv,RE} + I_t^{op,prod} + I_t^{op,stor} + I_t^{op,trans} + I_t^{op,RE} + I_t^{import} + (\sum_{\chi\in \mathrm{X}} \Pr(\chi)\,(I_{t\chi}^{var,trans} + I_{t\chi}^{var,res} + I_{t\chi}^{spot}) \tag{7.1}$$

Equations (7.2) represents the central constraint of the model, energy/material balance, where β_{om} is binary, indicating whether the resource m can be obtained from the origin o and α_{mp} denotes the conversion rate of the resource m by production technology p. Accordingly, in each region and time period, the total supply, comprising fuel production, net storage changes, transportation flows, and contracted as well as spot imports, must meet the corresponding regional demand in each period.

$$\sum_{O\in O} \beta_{om}\omega_{oits\chi} + \sum_{p\in P} \alpha_{mp}\, x_{pits\chi} + \sum_{L\in L|(l,m)\in A_{lm}} \left(y_{lmit(s-1)\chi} - y_{lmits\chi}\right) + \sum_{i'\in I} \sum_{q\in Q|(q,m)\in B_{qm}} \left(z_{qmi'its\chi} - z_{qmii'ts\chi}\right) + \psi_{mits}^{import} + \Psi_{mits\chi}^{spot} \geq D_{mits}, \qquad m\in M, \quad i\in I, \quad t\in T, \quad s\in S, \quad \chi\in X \tag{7.2}$$

In addition, the model incorporates several technical and resource-related limitations. Contracted imports are restricted to not exceed the permitted import shares (Equation (7.3)). The output of each production technology is bounded by its installed capacity (Equation (7.4)). Storage quantities also cannot surpass the installed storage capacity and are limited to compatible storage types at designated locations e.g., caverns (Equation (7.5)). Transportation of resources via modes requiring infrastructure investment is constrained by the installed capacity and is only feasible between regions where pipeline construction is possible, ensuring the correct assignment of transportation modes (Equations (7.6) and (7.7)).

$$\sum_{i\in I}\sum_{s\in S} \psi_{mits}^{import} \leq \upsilon_{mt}, \qquad m\in M, \quad t\in T \tag{7.3}$$

$$x_{\mathrm{Pits\chi}} \leq H'\, K_p^{prod}\delta_{pit}, \qquad p\in P, \quad i\in I, \quad t\in T, \quad s\in S, \quad \chi\in \mathrm{X} \tag{7.4}$$

$$y_{lmitsχ} \leq K_l^{stor} \gamma_{lit}\,, \quad t \in T, \quad s \in S, \quad \chi \in \mathrm{X}, \quad (l,m) \in A_{lm}\,, (l = caverns \rightarrow i \in CI) \wedge (l \neq caverns \rightarrow i \in I) \tag{7.5}$$

$$z_{qmii'tsχ} \leq HK_q^{trans} \kappa_{qii't}\,, \quad q \in Q_{inv}, \quad m \in M, \quad i,i' \in I, \quad t \in T, \quad s \in S, \quad \chi \in \mathrm{X} \tag{7.6}$$

$$z_{qmii'tsχ} = 0, q \in Q, \quad m \in M, \quad i,i' \in I, \quad t \in T, \quad s \in S, \quad \chi \in \mathrm{X} \mid B_{qm} = 0 \wedge i \neq i' \wedge B_{ii'}^{pipe} = 0 \wedge B_{ii'}^{truck} = 0 \tag{7.7}$$

Resource utilization is capped by the available potential of resource origins (Equation (7.8)). Similarly, the use of renewable electricity from wind and solar power is limited by the installed capacity in each region, adjusted by the seasonal capacity factor and the number of hours per season (Equation (7.9)). Furthermore, the installation of onshore and offshore wind and solar power is restricted by region-specific maximum installable capacities (Equation (7.10)).

$$\omega_{oitsχ} \leq \mathrm{R}_{oist}\,, \quad o \in O \setminus RE, \quad i \in I, \quad t \in T\,, \quad s \in S, \quad \chi \in \mathrm{X} \tag{7.8}$$

$$\omega_{oitsχ} \leq H\theta_{itr}\vartheta_{isrχ}\,, \quad o \in RE, \quad i \in I, \quad t \in T, \quad s \in S, \quad \chi \in \mathrm{X} \tag{7.9}$$

$$\theta_{itr} \leq \Theta_{ir}\,, \quad r \in RE, \quad i \in I, \quad t \in T \tag{7.10}$$

Finally, the number of installed production, storage, and transportation facilities, as well as renewable energy infrastructures, must remain non-decreasing over time and persist throughout the planning horizon (Equation (7.11-14)). The variable types are specified in Equations (7.15) to (7.17).

$$\delta_{pi(t-1)} \leq \delta_{pit}\,, \quad p \in P, \quad i \in I, \quad t \in T_0 \tag{7.11}$$

$$\gamma_{li(t-1)} \leq \gamma_{lit}\,, \quad l \in L, \quad i \in I, \quad t \in T_0 \tag{7.12}$$

$$\kappa_{qii'(t-1)} \leq \kappa_{qii't}\,, \quad q \in Q_{inv}, \quad i,i' \in I | i \neq i', \quad t \in T_0 \tag{7.13}$$

$$\theta_{i(t-1)r} \leq \theta_{itr}\,, \quad r \in RE, \quad i \in I, \quad t \in T_0 \tag{7.14}$$

$$\theta_{itr}, \psi_{mit}^{import} \geq 0, \quad i \in I, \quad t \in T_0, \quad m \in M, \quad r \in RE \tag{7.15}$$

$$\kappa_{qii't\chi}, \delta_{pit\chi}, \gamma_{lit\chi} \in \mathbb{N}_0\,, \quad q \in Q_{inv},\ p \in P,\ l \in L,\ i,i' \in I |\ i \neq i',\ t \in T_0,\ \chi \in \mathrm{X} \tag{7.16}$$

$$z_{qmii'ts\chi},\ x_{pist\chi},\ y_{lmits\chi},\ \omega_{oist\chi},\ \Psi_{mits\chi}^{spot} \geq 0, \quad q \in Q, \quad p \in P, \quad l \in L, \quad m \in M, \quad o \in O, \quad i,i' \in I | i \neq i', \quad t \in T, \quad s \in S, \quad \chi \in \mathrm{X} \tag{7.17}$$

7.4 Case study

We implement our method in a country-specific case study for Europe (EU+UK) to meet future transportation sector demand within the time frame of 2021 to 2060, aiming at climate neutrality. 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). As we

assume that this time horizon can be transferred to ten-year strategic periods, we structure our planning into decade-long intervals. In addition, we take into account four seasons to represent the availability of resources over a year. Seasons are defined as March–May (spring), June–August (summer), September–November (autumn), and December–February (winter). Production and transport facilities operate 1752 hours per season at an 80% capacity factor without spares (Larson et al., 2009).

Biomass supply by region and decade follows the ENSPRESO reference scenario (European Commission, 2019a), with seasonal availability determined by allocating individual products to their harvest periods (Čuček et al., 2014). For solar and wind (onshore and offshore), maximum installable capacities are taken from the reference scenario of ENSPRESO (European Commission Joint Research Centre, 2019b, 2019c). Hydrogen production is assumed to rely on freshwater, with national freshwater potential obtained from Eurostat (Ruiz et al., 2019). According to the FVV study (Report, 2021) 50% of the biomass and renewable electricity potential is assumed to be used. Biomass prices follow the ENSPRESO reference scenario, and water prices are taken from the governance of European water services (EurEau, 2020; Varone & Ferrari, 2015) and CO_2 prices from industrial and biogenic sources are based on (Brynolf et al., 2018).

We assume there are no fuel production facilities 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 from the FVV study (Report, 2021) and Vos et al. (Vos et al., 2020). Three capacity levels with associated costs are modeled for most technologies based on the FVV study. the smallest available in period 1, larger units in periods 2 and 4 to reflect technological progress in cost and scale. For Haber–Bosch, only two capacities are included from period 1 (Fasihi et al., 2021). DAC and ASU are represented by a single capacity available throughout. CAPEX and OPEX for RES are adopted from the FVV study (Report, 2021).

We model two pipeline capacities for CO2 (Fasihi et al., 2019; McCollum & Ogden, 2006) and three capacities for H2 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 CO2 from DAC, H2, FT-fuels, MeOH, and NH3,

with H2 caverns available only in selected countries (Bulgaria, Germany, Denmark, France, Netherlands, Poland, Portugal, UK).

Future European demand for renewable liquid fuels is projected to rise. FT-fuel demand follows the high-demand scenario (Siegemund et al., 2017). H2 demand is derived from EHB projections for aviation and heavy-duty transport (Wang et al., 2021). For MeOH, we adopt IRENA's global projections (IRENA AND METHANOL INSTITUTE, 2021) assigning 10% to Europe and 34% to fuels (Alvarado, 2016) implying higher demand than transport alone. Ammonia demand is based on IEA projections for transport-related N_2 use (IEA, 2021). Country-level demands are allocated proportionally to the population.

To achieve independence in energy provision and to account for the limited amount of imports available, in accordance with the FVV study (Report, 2021) we assume that no more than 30% of the fuel demand should be met by contracted imports. We also assume that spot import is allowed in scenarios where demand cannot be met internally or by contracted imports. However, there is a penalty cost higher than the contracted import for spot imports. We use the ratio of spot to contracted import prices for LNG markets since gas contracts are the current pricing mechanism across most of continental Europe (Asche et al., 2013). For the base case of this study, spot imports are assumed to have three times higher costs per tonne than contracted imports.

The model is being solved using the high-performance computing (HPC) center at RWTH Aachen University, utilizing 30 CPUs. To ensure timely results, we have set a max gap of 0.03. An overview of all the data used as parameters in our model for this case study, along with all references, is provided in the appendix.

7.4.1 RES variability

The weather conditions at the upstream end of the SC affect resources such as wind and solar power, resulting in varying availability of renewable electricity (Staffell & Pfenninger, 2016). Capacity factors represent the ratio of actual energy produced to the maximum possible output over a given period, serving as a key indicator of resource quality and reliability. Fluctuations in capacity factors arise from multiple interconnected factors. Intermittency in output and potential curtailment challenge the reliable use of wind and solar, often shifting focus from overall to incremental capacity factors. Uncertainty in load and demand complicates balancing generation and consumption, while equipment availability, maintenance requirements, and pol-

icy mechanisms, including emissions regulations and renewable energy incentives, further shape technology choices and capacity deployment strategies.

Figure 7-2 illustrates monthly average electricity demand and solar/wind capacity factors for Germany, based on 30 years of historical data (Electricity Data Explorer | Ember, 2024; Pfenninger & Staffell, 2016; Staffell & Pfenninger, 2016a, 2016b). As can be seen in the figure, each solid line represents monthly averages, while the shaded regions show the observed minimum and maximum values for each month through these 30 years of data. Solar and wind capacity factors exhibit pronounced fluctuations and a clear seasonal pattern, though their average values can be relatively low, whereas electricity demand remains within a more stable range. Nonetheless, these variable renewable resources must still be harnessed to reliably meet demand throughout the year, which can pose significant challenges for a renewable fuel SC in ensuring a consistent and sufficient supply. Based on the historical data shown in Figure 7-3 for 26 EU countries and the UK, we design scenarios based on RES's capacity factors, which directly affect the electricity supply.

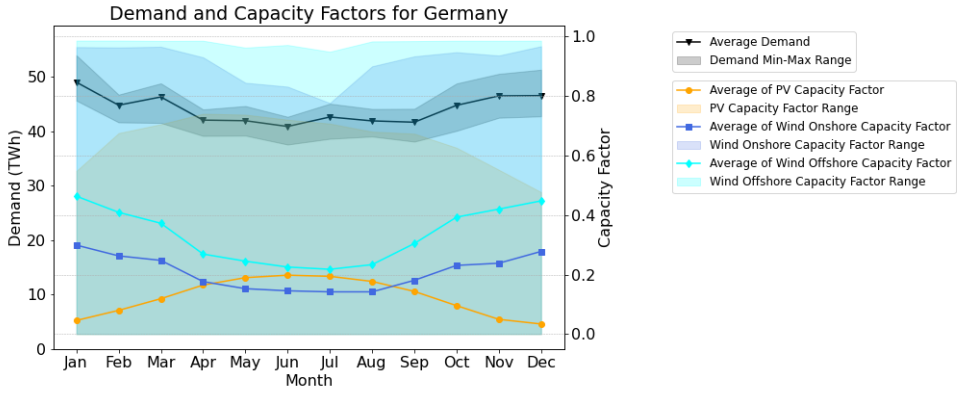


Figure 7-2: Monthly averages and variability ranges of electricity demand and solar and wind capacity factors for Germany based on (Electricity Data Explorer | Ember, 2024; Pfenninger & Staffell, 2016; Staffell & Pfenninger, 2016a, 2016b)

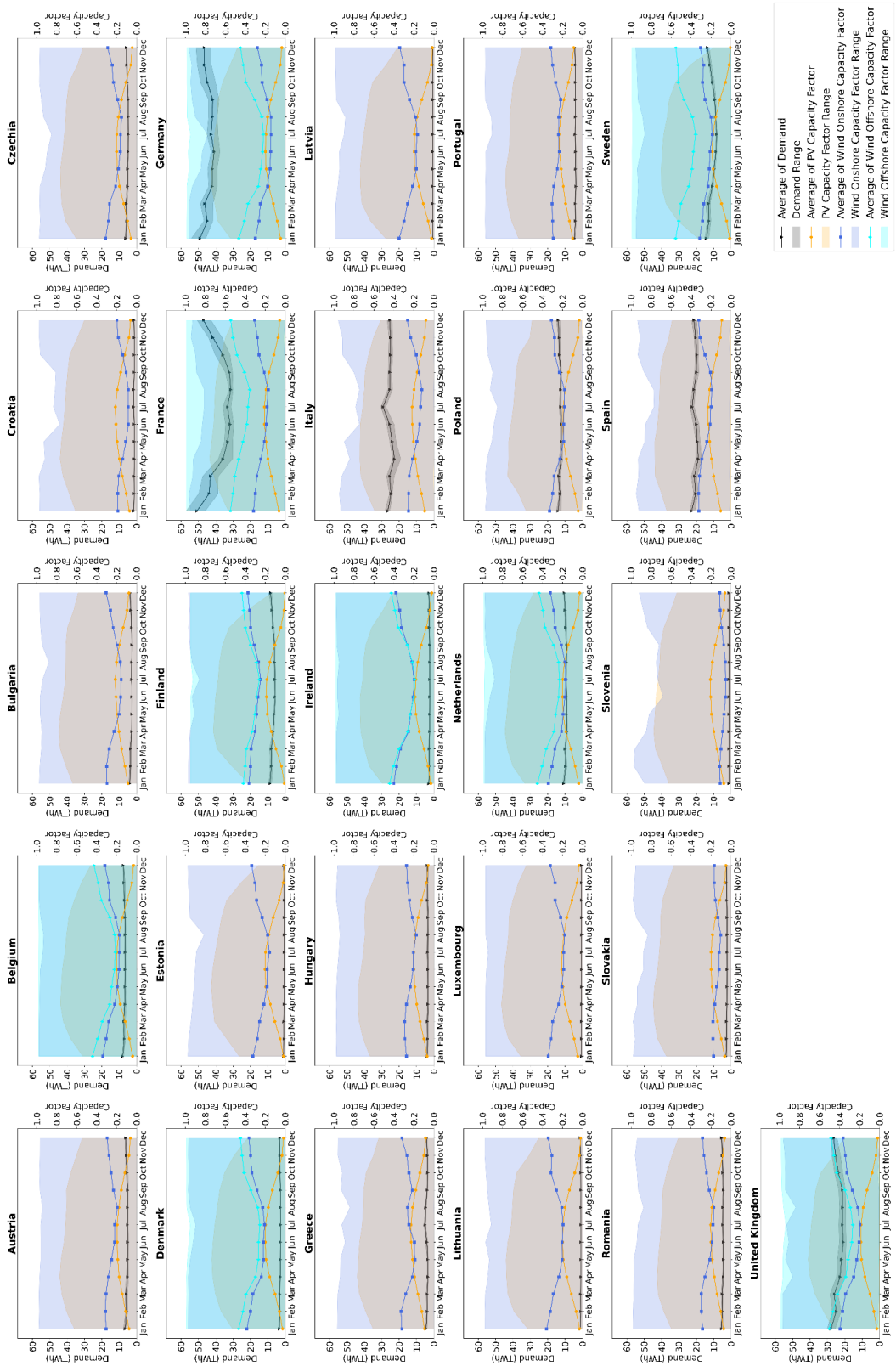


Figure 7-3: Monthly average and range of electricity demand and solar/wind capacity factors over 30 years based on (Electricity Data Explorer | Ember, 2024; Pfenninger & Staffell, 2016; Staffell & Pfenninger, 2016a, 2016b)

7.4.1.1 Scenario designs

In this study, we employ a scenario-based framework to consider uncertainty in renewable energy capacity factors, leveraging 30 years of historical data. The extensive historical period ensures our analysis encompasses diverse weather patterns and rare events, as well as regional correlations, offering a robust basis for modeling long-term seasonal variability. This extended dataset enhances statistical reliability by improving estimates of mean and variance for country-specific capacity factors and supporting accurate validation of the normal distribution assumption.

Our methodology proceeds through several structured steps. Initially, for each country and season, we calculate the mean and variance of solar, onshore wind, and offshore wind capacity factors from the 30-year historical dataset. A normal distribution is then fitted to these values and validated using the Kolmogorov-Smirnov test to confirm statistical significance. Subsequently, we discretize these continuous probability distributions into distinct scenarios using the percent point function (PPF) of the normal distribution. Specifically, we select the 33rd, 66th, and 99th percentiles to define scenarios representing low, medium, and high conditions, respectively. This approach strikes a balance between representing typical conditions and capturing extreme cases, optimizing computational efficiency.

As mentioned earlier, data is based on the renewable ninjas database (Staffell & Pfenninger, 2016). Following the scenario definition, we generate scenarios for multiple variables, addressing 244 uncertain factors. This includes solar and onshore wind capacity factors for 26 countries across four seasons and offshore wind capacity factors for 9 countries over the same periods. For each country-RES-season combination, three distinct scenarios are created, comprehensively covering the inherent variability. These scenarios are subsequently structured into a scenario tree spanning four strategic periods. With three scenarios per period, the scenario tree contains 81 (34) unique pathways. Each node within the tree signifies a specific system state at a given time, while arcs between nodes represent probabilistic transitions. Node probabilities are determined by multiplying probabilities along the path from the root, ensuring probabilities at each stage sum to one. This framework visually represents all possible outcomes of the stochastic process over the entire planning horizon.

While a higher number of scenarios could offer more precise uncertainty modeling, we intentionally limit their number to maintain a practical balance between accuracy and computational feasibility. This scenario tree seamlessly integrates into our decision-making frame-

work, significantly enhancing strategic planning robustness. The combination of an extensive historical analysis and a carefully constructed scenario framework strengthens both methodological clarity and practical applicability for decision-making under uncertainty. The values for scenarios can be found in the supplementary material.

Later in the paper, we present results from three extreme scenarios to highlight their differences. Sc1 has the lowest values for all capacity factors, Sc41 has medium values, and Sc81 has the highest capacity factor values. Figure 7-4 shows the structure of the generated scenario tree.

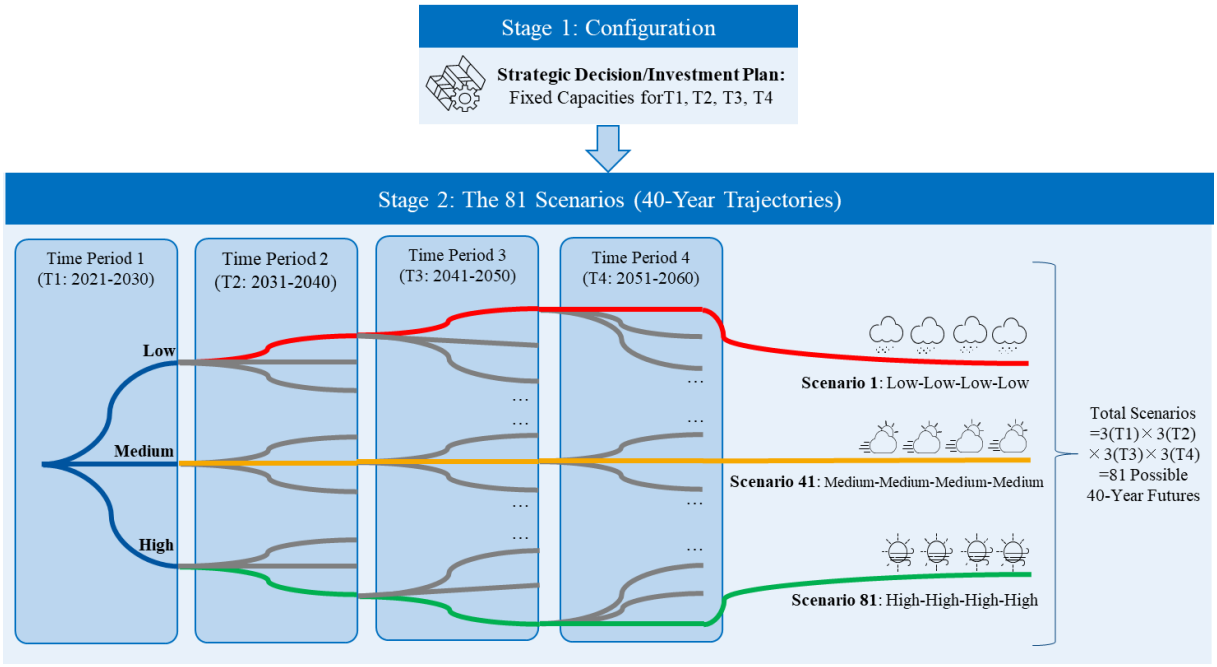


Figure 7-4: Overview of scenarios

7.5 Results

To gain a deeper understanding of the TSSP model, we now provide a more detailed analysis of its solution. Figure 7-5 illustrates the installed capacity of solar and wind power over strategic time periods. The results reveal a significant growth in both solar and wind installations across EU countries. PV installations see a steady rise, particularly in countries like Italy, Spain, and France, which become leaders in PV deployment by the fourth decade. Similarly, wind installations experience notable growth, with countries such as the UK, Spain, and Germany dominating in the later periods. Countries like Poland and Romania also emerge as significant contributors in both sectors during the third and fourth decades. The overall trend indicates that while solar energy installations had a stronger early focus in southern and central Europe, wind energy gains traction across northern and western EU, aligning with favorable

geographic conditions. The country with the fastest growth in both solar and wind installations is France from the first to the fourth decade. In this case study, RES is installed up to the permitted potential in most countries, which explains why the installation amount in the last period is significantly lower. The remaining strategic (first-stage) decisions are provided in the supplementary material.

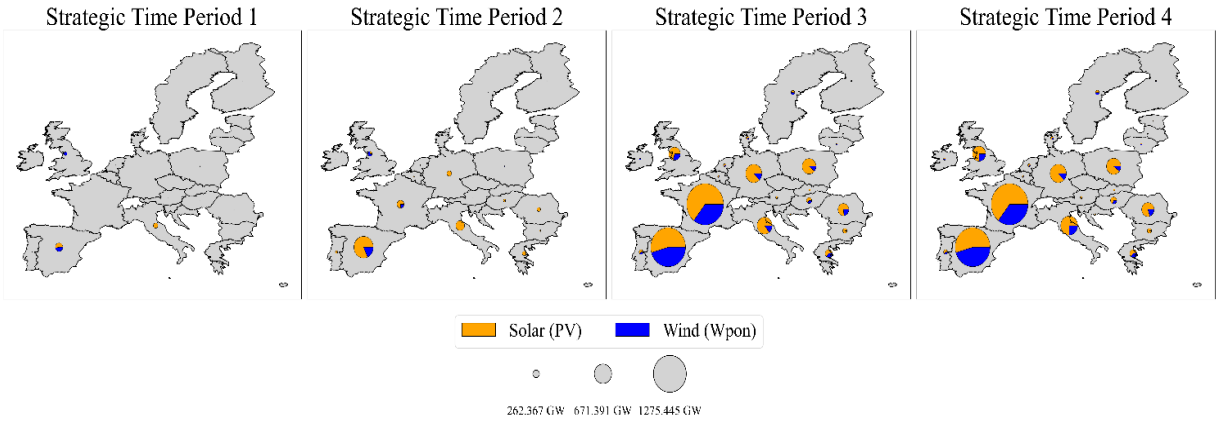


Figure 7-5: Expansion of installed solar and wind capacities in EU+UK over strategic time periods for TSSP solution

Table 7-2 shows the amount of contracted imports of fuels over strategic time periods and the share of this amount relative to the maximum allowed contracted import across the strategic time periods. T4 dominates overall import usage, making up more than 90% of the total imports (roughly 136 million out of 150 million). FT-fuel alone is contributing over two-thirds of the total imports, spiking from about 5 million in T3 to 103 million in T4, which corresponds to 92% of its allowable import capacity. This reflects insufficient domestic production capacity at this time period. MeOH follows with a total of around 32 million imports. Again, this is concentrated heavily in T4 (27.5 million), reaching 45% of its capacity and averaging 26% across all periods. NH_3 and H_2 remain comparatively small in absolute terms at around 3.8 million and 4.2 million, respectively. However, again, both show significant increases between T3 and T4. H2, in particular, jumps from 164k in T3 to over 4 million in T4, translating into an 81% utilization rate and the highest average of all time periods across fuels (49%). NH_3, by contrast, peaks at 14% in T1 and averages just 3% overall, indicating heavy reliance on domestic supply. Overall, import utilization remains limited in early periods, 6% in T1, 2% in T2, and 6% in T3, but surges to 54% in T4 across all fuels. This shift reflects both rising demand and the exhaustion of RES installation capacities, which makes imports essential to meet residual needs.

Table 7-2: Amount of contracted imports over strategic time periods for TSSP solution [thousand tonne/season]

	T1		T2		T3		T4		Total	
Fuels	**Value**	**%**	**Value**	**%**	**Value**	**%**	**Value**	**%**	**Value**	**%**
NH_3	782	13.8	250	2.2	1,004	2.4	1,728	2.3	3,763	2.8
FT-fuel	742	4.3	909	2.4	4,960	5.6	102,988	91.6	109,600	42.6
H_2	199	0.2	0	0.0	164	6.1	4,045	80.5	4,209	48.7
MeOH	595	5.0	414	2.8	3,727	9.8	27,548	45.0	32,285	25.7
Total	2,120	6.0	1,573	2.4	9,855	5.7	136,309	53.9	149,857	28.5

For tactical (second-stage) decisions, Figure 7-6 depicts the utilization of the resources over strategic time periods. Across these resources, Sc1, despite having the highest total costs and lowest capacity factors, is not always strictly greater than Sc81, which has the lowest total costs and highest capacity factors. Although Sc1 utilizes higher biomass in all time periods, water usage is notably higher under Sc81 throughout T1–T4. For CO_2 from cement, Sc81 begins higher at T1, but Sc1 surpasses it in later periods, despite a slight drop in T4. With CO_2 from biogenic sources, Scenario 81 starts out higher in T1 and T2, but by T3 and T4, Scenario 1 takes the lead, yet both remain in roughly the same range. As expected, Sc41 shows values that fall between those of the two extremes.

Relative to available resources, utilization generally increases over time. Biomass use rises from 57% (Sc1), 54% (Sc41), and 52% (Sc81) in T1 to 96%, 94%, and 78% in T4, respectively. Water utilization remains minimal, staying below 1% across all time periods and scenarios. CO_2 Industry shows a sharp increase in Sc1 from 2% in T1 to 86% in T3, and slightly declining to 84% in T4. Sc41 follows a similar pattern but with lower values, starting at 2% in T1 and peaking at 76% in T4. Sc81 starts slightly higher at 3% in T1 and reaches 82% in T3, but then drops significantly to 52% in T4. For CO_2 Biogenic, Sc81 starts at 40% in T1 and maintains over 94% from T3 to T4. Sc41 begins at 38% and steadily rises to 94% in T4. Sc1 starts at 35% in T1 and peaks at 99% in T3, slightly decreasing to 98% in T4.

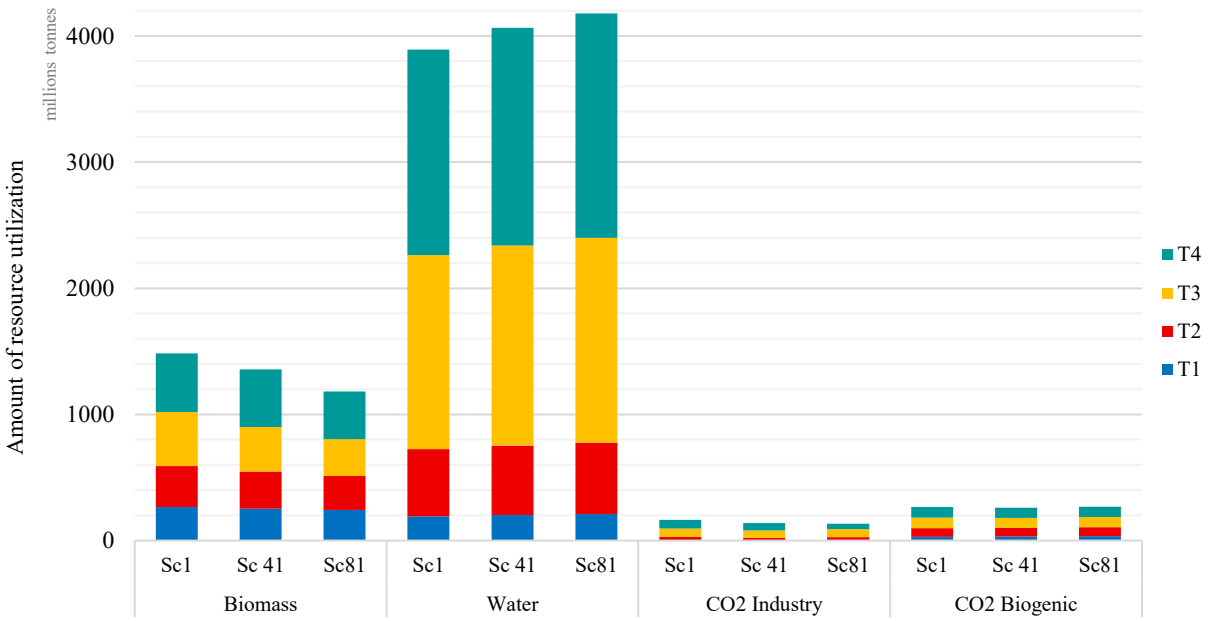


Figure 7-6: Resource utilization over strategic periods under three scenarios for the TSSP solution

Figure 7-7 shows the production amount of fuels for each technology. For H_2 production, the share from AEL technology is 50% in Sc1, declining to 47% in Sc81, with the reduction offset by increased production from PEM, which generally offers higher efficiency and capacity factors. In FT-fuel production, BtL accounts for 11% in Sc1, falling to 7% in Sc81, while PBtL decreases from 25% to 23%. In contrast, PtL technologies rise from 65% in Sc1 to 70% in Sc81, benefiting from greater renewable electricity availability and lower production costs. For MeOH production, BtL's share drops from 25% to 19% between Sc1 and Sc81, whereas PtL increases from 15% to 19%, and PBtL rises from 60% to 62% over the same scenarios. This shift from using costlier or less efficient technologies (AEL, BtL) forced by low electricity availability in Sc1 toward technologies with lower costs (PEM, PtL, PBtL) enabled by high electricity availability in Sc81 explains why Sc1 has the highest total costs, resulting from its lowest capacity factors, while Sc81 achieves the lowest costs, resulting from its highest capacity factors. The remaining tactical (second-stage) decisions are presented in the supplementary material.

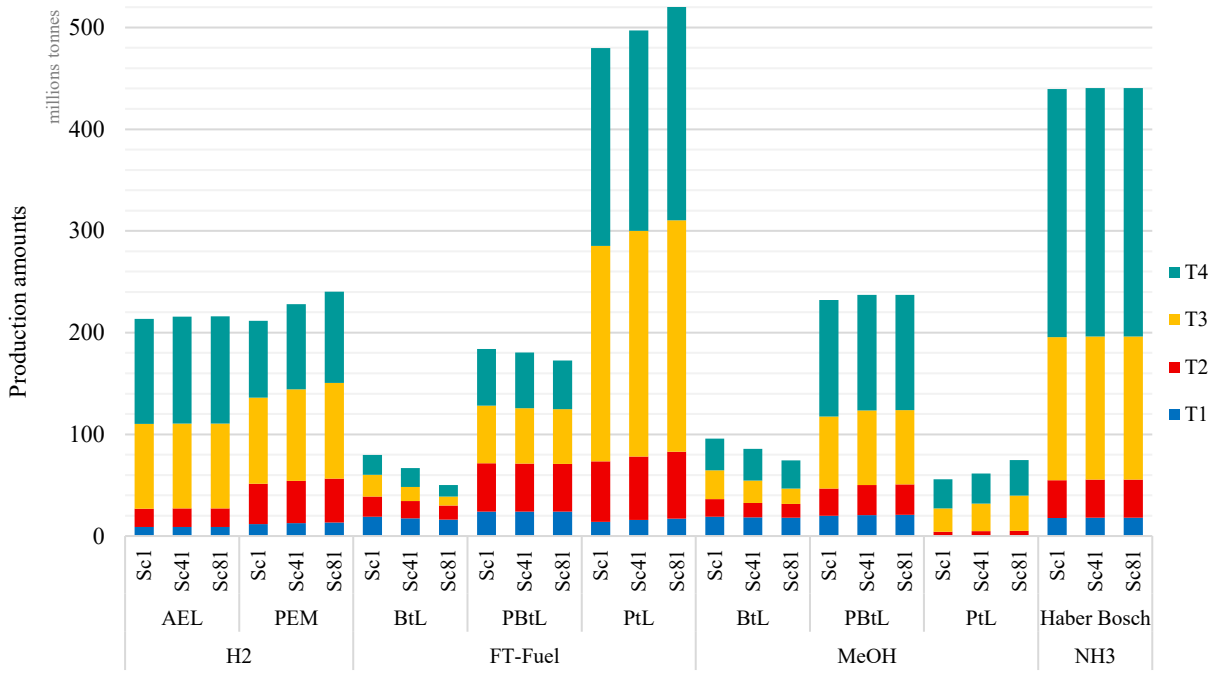


Figure 7-7: Production amounts of fuels over strategic periods under three scenarios for the TSSP solution

7.5.1 Sensitivity analysis of import parameters

The following analysis investigates how the import parameter values affect the stochastic model's results. According to the base case, the cost of spot import is set to three times the contracted import. To assess the importance of spot import cost, we consider 5 and 10 as other ratios to analyze the effect on spot imports and costs. Table 7-3 presents the objective function for each ratio solved using our TSSP model.

Table 7-3: Objective function of different spot import cost ratios [trillion €]

Ratios	Ratio3	Ratio5	Ratio10
Expected value of total costs	10.69	10.73	10.75

Our analysis of their cost structure reveals that overall, Production Investment and RES Investment follow similar trajectories across Ratio3, Ratio5, and Ratio10. The transportation & storage investment remains quite small compared to other items, and in some cases dips as low as zero in T4 (notably under Ratio3). Meanwhile, production O&M and RES O&M each see their highest spending in T3, with only modest differences among the three ratio scenarios, suggesting the choice of ratio does not dramatically reshape these costs. Obviously, the most striking change appears in contracted imports. Higher ratios tend to increase costs across most categories.

Table 7-4 shows that spot import costs decline substantially when moving from Ratio3 to Ratio10. For example, in Sc1, the spot import cost in T4 decreases from almost 413 billion € (Ratio3) to 151 billion € (Ratio5) and further to 122 billion € (Ratio10). A similar trend is visible in earlier periods, where spot imports vanish entirely in Ratio10. This confirms that higher spot import penalties lead the model to reduce reliance on spot markets, instead shifting toward contracted imports and domestic production. At the same time, overall contracted import costs increase slightly across ratios, and RES investments rise marginally as well, indicating a deliberate substitution effect. The decrease in spot imports, therefore, explains a major part of the increase in total expected costs between Ratio3 and Ratio10, as the system pays more for domestic and contracted options to avoid very expensive spot purchases in the low capacity factor scenarios.

Table 7-4: Second stage costs of different spot import cost ratios [billion €]

Cost Items	Scenarios	T1			T2			T3			T4		
		Ratio3	Ratio5	Ratio10	Ratio3	Ratio5	Ratio10	Ratio3	Ratio5	Ratio10	Ratio3	Ratio5	Ratio10
Bio-mass	**Sc1**	146.9	145.3	145	144.9	145.4	145.4	163.8	164.6	164.4	130.9	130.3	129.6
	Sc41	139.8	137.3	137.4	124.9	124.6	124.8	117.5	116.4	115.4	125.9	97.2	89.9
	Sc81	133.2	131.8	133.5	111.4	110.7	110.5	97.6	98.4	97.9	96.3	70.8	65.7
Spot Import	**Sc1**	65.7	36.8	14	9.9	-	-	17.1	6.9	-	412.9	151	122.3
	Sc41	1.7	-	-	-	-	-	-	-	-	26.4	-	-
	Sc81	-	-	-	-	-	-	-	-	-	-	-	-
Total 2nd-Stage	**Sc1**	226.3	196.5	173.7	184.3	174.7	174.4	222.5	213.3	206.1	571.9	308.8	279.1
	Sc41	156.4	152.6	152.9	152.6	151.9	152.1	157.3	156.5	155.4	180.5	125.1	115.6
	Sc81	148.8	148.2	149.7	141.2	140.4	139.9	139.3	140.4	139.9	123.3	97.6	92.5

Table 7-5 shows the expected amount of spot imports in each of these cases. The last column shows the expected spot import cost for each case. Ratio3 uses spot imports broadly and at higher levels, while Ratio5 adopts a moderate mix. Ratio10 uses spot imports of MeOH, with minimal or no spot imports of H_2 or other fuels, indicating a more selective strategy. In Ratio 5, the total expected volume of spot imports decreases by 71%, while the associated cost decreases by 64% compared to the base case. In Ratio 10, spot imports are reduced by 84% in volume and 74% in cost, again relative to the base case.

Table 7-5: Expected spot import amounts and costs in different spot import cost ratios [thousand tonne/season]

Ratio	Fuels	T1	T2	T3	T4	Total amount	Expected total spot import cost
Ratio3	NH_3	143.4	29.3	28.7	52.8	254.2	
Ratio3	FT-fuel	22.4	15.9	33.5	340.4	412.1	176.17
Ratio3	H_2	0.1	0	0	3,008.2	3,008.4	billion €
Ratio3	MeOH	48.9	0	122.1	1,025.2	1,196.2	
Ratio5	NH_3	50.3	0	0	25.5	75.7	
Ratio5	FT-fuel	0	0	2.2	141.7	143.9	64.28
Ratio5	H_2	0	0	0	368.7	368.7	billion €
Ratio5	MeOH	23.8	0	54.3	757.6	835.7	
Ratio10	NH_3	0	0	0	11.8	11.8	
Ratio10	FT-fuel	0	0	0	80.4	80.4	44.99
Ratio10	H_2	0	0	0	0	0	billion €
Ratio10	MeOH	22.7	0	0	680.4	703.2	

This analysis of spot import price ratios highlights how the system adapts to rising spot prices. As the ratio increases, investments shift more strongly toward domestic production, reducing exposure to costly spot imports. While the structure of production and RES investments remains broadly similar, contracted imports rise with higher ratios, and spot imports become concentrated in specific fuels (notably MeOH under Ratio 10). Importantly, despite these shifts, the overall system cost increases only moderately, indicating that the model effectively reallocates resources through higher domestic capacity or contracted imports to manage the risks of expensive spot markets.

We also investigate the impact of the allowed share of imports. In the base case, 30% of demand could be met by contracted imports. We additionally examine shares of 10% and 50%. Table 7-6 shows these results.

Table 7-6: Objective functions of different contracted import shares [trillion €]

Shares	Share of 10%	Share of 30%	Share of 50%
Expected value of total costs	11.09	10.69	10.63

As we analyze their cost structure, we find that share10% tends to allocate more heavily to production investment and production O&M while still keeping contracted import at a substantial but lower figure in T4. Obviously, share30% and especially share50% are directed more toward contracted imports. The same split comes up in RES investment: all shares spike in T3, but share10% reaches the highest mark, while share50% comes in lowest. These highlights

suggest that Share10% leans more toward domestic production and renewables, whereas share30% and share50% gradually shift resources into imported supply.

Table 7-7 shows the utilization rates of contracted imports relative to their permitted maximum across fuels and time periods. The analysis of contracted import utilization shows that the model does not always fully exhaust the permitted amounts, and the extent of utilization varies across fuels and import shares. In the Share10%, contracted imports are used almost entirely in later periods, with fuels such as H_2 and MeOH reaching over 90% of the allowed volumes in T4, resulting in overall utilization levels of around 50%. In Share30%, the utilization is more moderate, with contracted imports often falling short of the maximum (e.g., MeOH at 25.7% of allowed volumes and H_2 at 48.7% on average). In Share50%, the model makes even less use of the permitted imports, particularly for MeOH (12.9%) and fuels (29.3%), despite the higher allowance. This indicates that while the option of contracted imports is valuable, the model strategically balances them with domestic production and other supply sources, and the relative utilization decreases as the permitted share increases.

Table 7-7: Share of contracted imports relative to the maximum allowed contracted imports

Share	Fuels	T1	T2	T3	T4	Total
Share 10%	NH_3	12.9%	2.1%	0.9%	4.1%	3.3%
Share 10%	FT-fuel	10.8%	2.2%	1.4%	96.1%	43.5%
Share 10%	H_2	8.8%	0.0%	0.0%	92.3%	53.8%
Share 10%	MeOH	9.9%	3.9%	3.7%	95.8%	49.1%
Share 30%	NH_3	13.8%	2.2%	2.4%	2.3%	2.8%
Share 30%	FT-fuel	4.3%	2.4%	5.6%	91.6%	42.6%
Share 30%	H_2	0.2%	0.0%	6.1%	80.5%	48.7%
Share 30%	MeOH	5.0%	2.8%	9.8%	45.0%	25.7%
Share 50%	NH_3	13.5%	0.5%	0.6%	0.9%	1.3%
Share 50%	FT-fuel	1.7%	1.0%	5.8%	61.9%	29.3%
Share 50%	H_2	0.2%	0.0%	5.8%	82.0%	49.5%
Share 50%	MeOH	3.9%	2.4%	9.3%	19.3%	12.9%

Table 7-8 shows a comparison of the capacity installation for these three cases. Across all import share levels, the installed capacity of PV installations consistently exceeds installed wind capacity, especially in later periods (T3–T4). Notably, higher import shares (e.g., 50%) tend to correlate with slightly lower wind expansions but comparable or slightly higher PV totals. Overall, the data suggest that, as the import share rises, the system leans more on solar capacity rather than wind, yet PV remains the dominant technology across all scenarios.

Table 7-8: Amount of RES installation in different contracted import shares [GW]

Share	RES	T1	T2	T3	T4	Total
Share 10%	PV	356	1,499	2,751	237	4,843
Share 10%	WP	288	61	1,688	209	2,245
Share 30%	PV	324	1,465	2,814	206	4,810
Share 30%	WP	293	98	1,523	78	1,991
Share 50%	PV	351	1,391	2,990	100	4,831
Share 50%	WP	279	138	1,341	10	1,768

The analysis of varying import share levels reveals trade-offs between domestic investment and reliance on imported supply. A lower import share (10%) drives significantly higher investment in domestic production infrastructure, and RES peaking most prominently in T3. In contrast, higher import shares shift the system's focus toward contracted imports, reducing the need for domestic capacity expansion. Cost-wise, increasing the import share from 10% to 30% results in a substantial reduction in total expected costs. However, the further reduction from 30% to 50% is minimal, dropping only slightly. Technology-wise, PV installations consistently dominate all cases. While higher import shares are associated with slightly lower wind deployment, PV remains the preferred renewable option regardless of import policy.

To further assess the impact of import costs, we analyzed a case in which import costs per tonne were doubled relative to the reference rate, which we use in the base case. Under this assumption, the TSSP model yields a total cost of 11.89 trillion €, representing a 10.9% increase compared to the base case. Among the scenarios, Sc1 yields the highest expected total costs at €12.56 trillion €, while Sc81 achieves the lowest at €11.51 trillion €. The spread between these extremes amounts to a 9% variance, highlighting the financial impact of scenario uncertainty.

Figure 7-8 presents these first-stage costs next to the base case results. Each pair of bars represents the contribution of cost items to the total cost. The height of the bars reflects the cumulative cost over four strategic time periods. Above each pair of bars, the percentage change from the base case to the Doubled is displayed. Notably, Contracted Import costs increased by approximately 44.5%. In contrast, Transportation & Storage Investment and O&M costs showed negative changes. Our analysis reveals that period 3 demands the highest overall investment and operational expenditures, driven primarily by investments in renewable electricity and substantial production and maintenance costs, which together account for over 84 percent of the total. Period 4 shifts the cost composition dramatically, featuring a huge spike in imports that eclipses investments in domestic production and renewables. Across all time periods, stor-

age and transportation costs remain negligible, below 0.1% of total spending, highlighting the predominance of production and RES investment in determining the system's economic footprint.

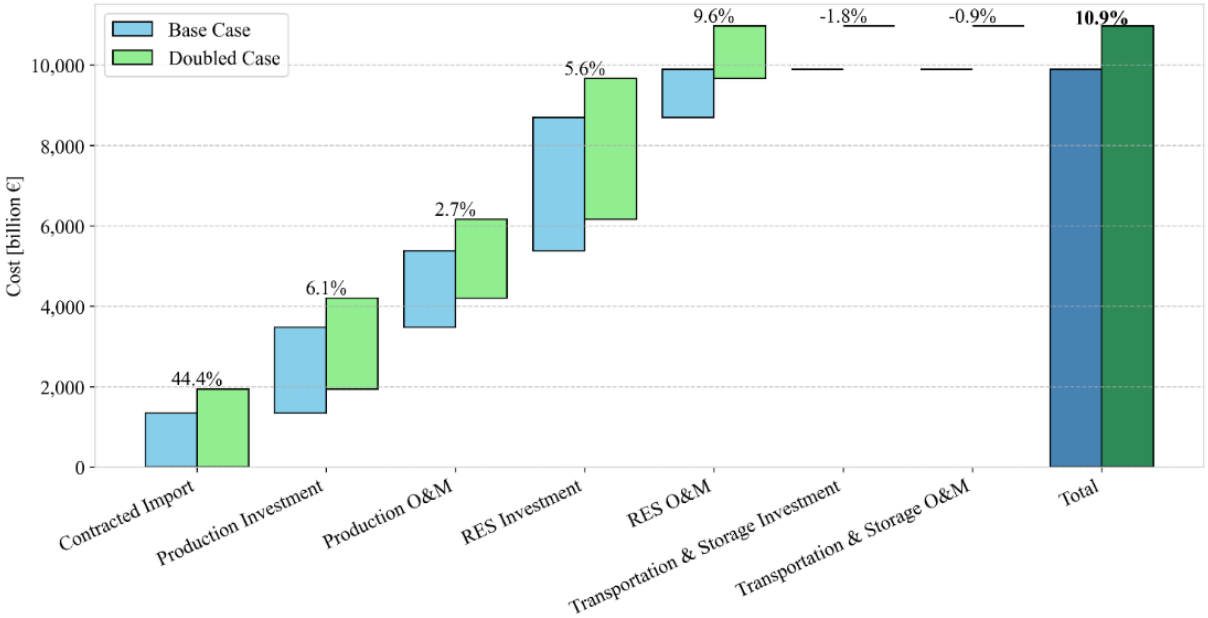


Figure 7-8: First-stage costs for the case with doubled import costs and the base case

Figure 7-9 presents the distribution of second-stage costs across all scenarios. The analysis reveals varying responses of cost components to doubling the base case. Unit Transport experienced the average percentage increase of +6.1%. CO_2 and Water costs also increased slightly by 3.0% and 2.6% respectively. In contrast, biomass costs decreased by an average of 3.6%. Spot Import saw the largest absolute change (+142 billion €), but percentage calculations are unreliable due to zero or near-zero values in some scenarios. Time-based analysis indicates that spot import costs are significantly higher compared to the costs of investments in excess domestic RES capacities. Costs vary considerably, spanning a 9% range, from sharp peaks in Sc1 to a balanced profile in Sc41 and the lowest values in Sc81. Overall, at Sc1, costs peak sharply in T3 before easing in T4, driven largely by high spot import costs and biomass expenditures. Sc41 exhibits a more balanced cost profile, with its highest cost shares concentrated in T2 and T3. Sc81 achieves the most stable and lowest cost outcomes, supported by higher renewable capacity factors and stronger domestic production.

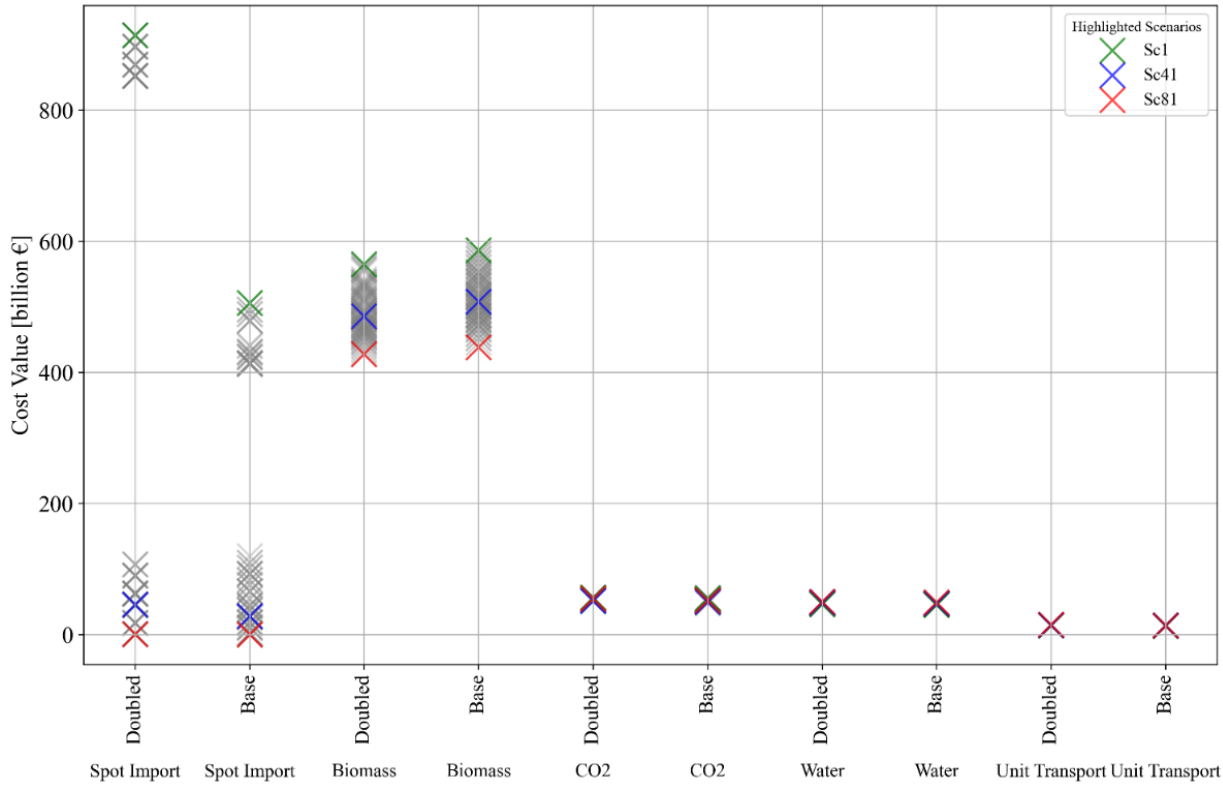


Figure 7-9: Second-stage costs for the case with doubled import costs per tonne

The analysis of the doubled import cost case underscores the system's sensitivity, with total costs rising by 11% compared to the base case. Higher import prices drive a shift toward domestic supply, with RES investment increasing markedly in periods 1–3 and production investment more than doubling in period 4 after an initial decline. O&M costs also rise in later periods, reflecting the late expansion of domestic capacity. While scenario variation indicates some cost volatility, overall results point to the stabilizing effect of stronger domestic reliance, underscoring the importance of strategic planning to mitigate price risks and enhance long-term system resilience.

7.5.2 Performance evaluation

In this section, we evaluate the proposed stochastic model. The expected value of total system costs across all scenarios is 10.69 trillion €. In the TSSP model, this value is calculated by weighting each scenario's total system cost by its associated probability and summing these weighted values.

Figure 7-10 presents a comparison of the objective function values of different modeling approaches. Where EV (Expected Value solution) is when the model is solved deterministically using expected values of uncertain parameters. While EV often appears cost-efficient, it is not robust because it ignores uncertainty and does not hedge against deviations from the average

value of uncertain parameters. WS (Wait-and-See solution) represents the perfect-information benchmark where each scenario is optimized individually as if future uncertainty were known in advance. It provides the lowest possible costs but is not feasible in practice, since perfect foresight is never available. EEV (Expected result of the Expected Value solution) evaluates the performance of the EV solution across all scenarios, thereby putting it on the same footing as the stochastic solution (TSSP) (Birge, 1982). Unlike EV and WS, the EEV provides a fair comparison to the stochastic model because both are assessed under uncertainty. Thus, although EV and WS may show lower objective values in a minimization problem, they are not practically usable under uncertainty. The EEV, in contrast, highlights the performance loss of a deterministic strategy when uncertainty is realized, and therefore provides the relevant benchmark against which the TSSP solution should be compared. The deterministic EV solution yields costs that are 4.7% lower than the TSSP solution. The WS solution results in a cost reduction of 4.5% compared to the TSSP solution. Conversely, adopting the EEV approach leads to a cost increase of 3.4%.

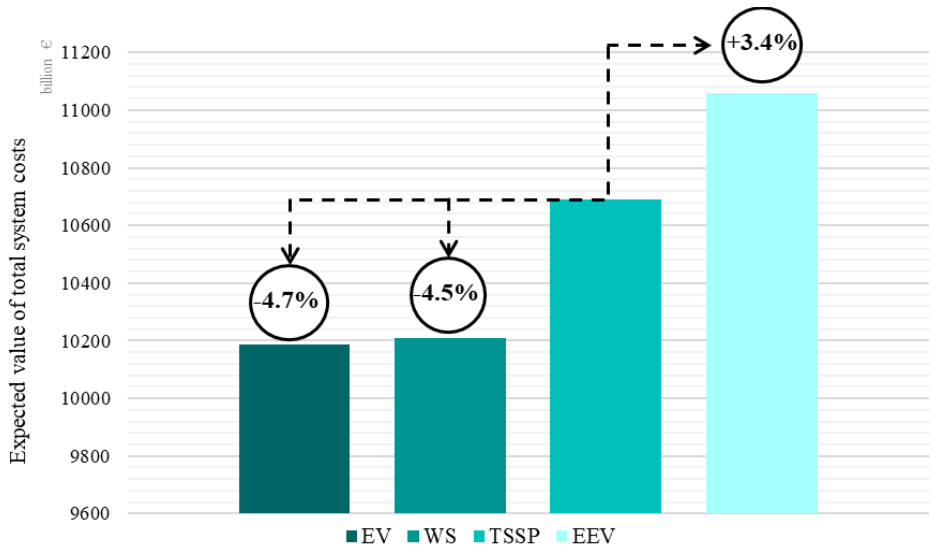


Figure 7-10: Expected value of the total system cost for different approaches

To assess the advantages of stochastic modeling over deterministic methods, we calculate two key metrics: the Value of the Stochastic Solution (VSS) and the Expected Value of Perfect Information (EVPI). The VSS is defined as the difference between the optimal objective value of the TSSP solution and the objective value obtained when first-stage decisions are fixed to those of the deterministic solution (the EEV), and measures the benefit of explicitly modeling uncertainty. The EVPI quantifies the maximum potential value of having complete information about all uncertainties before decision-making (Birge & Louveaux, 2011). In our case study,

the EVPI is 482.9 billion €, corresponding to 4.5% of the total system costs of TSSP, while VSS is 368.2 billion €, yielding a relative VSS (RVSS) of 3.4%. These substantial values demonstrate the clear advantage of employing stochastic programming with our TSSP model rather than relying solely on a deterministic formulation for our case study.

Figure 7-11 illustrates demand fulfillment for the fuels (FT-fuel, MeOH, H_2, NH_3) under the TSSP and EEV approaches across four strategic time periods. In both approaches, production remains the backbone of supply, but important differences emerge in later periods and under high-stress scenarios. In the EEV approach, demand is almost fully met by production in early periods. In T4 under Sc41 and Sc81, for example, FT-fuel and MeOH show that production covers approximately 88–93% of demand, while contracted and spot imports, as well as storage, collectively rise to fulfill the remaining 7–12%. For NH_3 and H_2, the contribution of non-production sources remains negligible (below 3%).

The TSSP model demonstrates the highest dependence on external and flexible fulfilment sources, particularly in late periods and stress scenarios. In T4 under Sc81, for example, MeOH demand is met by local production for only 70–75%, with contracted imports and spot imports fulfilling up to 20–25%, and storage and transportation accounting for the remaining 5–10%. For FT-fuel in TSSP and in T4, production accounts for 75–80% of demand, contracted imports and spot imports for 15–20%, and storage/transport for 5%. While NH_3 and H_2 continue to rely mainly on production (typically 85–95%), there is a noticeable increase in imports, especially for NH_3 in T1 (up to 15–20% fulfilled by contracted imports/spot imports in some scenarios).

Across all models, the share of demand met by local production decreases as scenarios move from Sc1 to Sc81 and as the time period progresses from T1 to T4, indicating increased supply chain pressures and the need for more diverse sourcing strategies under higher stress or demand. Imports, spot imports, and storage/transport mechanisms are most significant for FT-fuel and MeOH in the WS and SP approaches, highlighting these fuels' greater vulnerability to supply constraints and the critical role of logistical flexibility. Conversely, NH_3 and H_2 maintain high production-based fulfilment across approaches and scenarios, reflecting either more robust domestic supply chains or lower volatility in their demand. In summary, the analysis demonstrates that while production forms the backbone of supply in all approaches and scenarios, stress conditions and future periods drive a transition towards greater use of imports, spot imports, storage, and transport, particularly for FT-fuel and MeOH, emphasizing the importance of flexible and resilient supply strategies for these fuels. The superiority of TSSP over EEV

arises from its explicit treatment of uncertainty in capacity factors, which enables the model to anticipate stress conditions more effectively and to mitigate their impacts through earlier investments and enhanced flexibility in demand fulfillment.

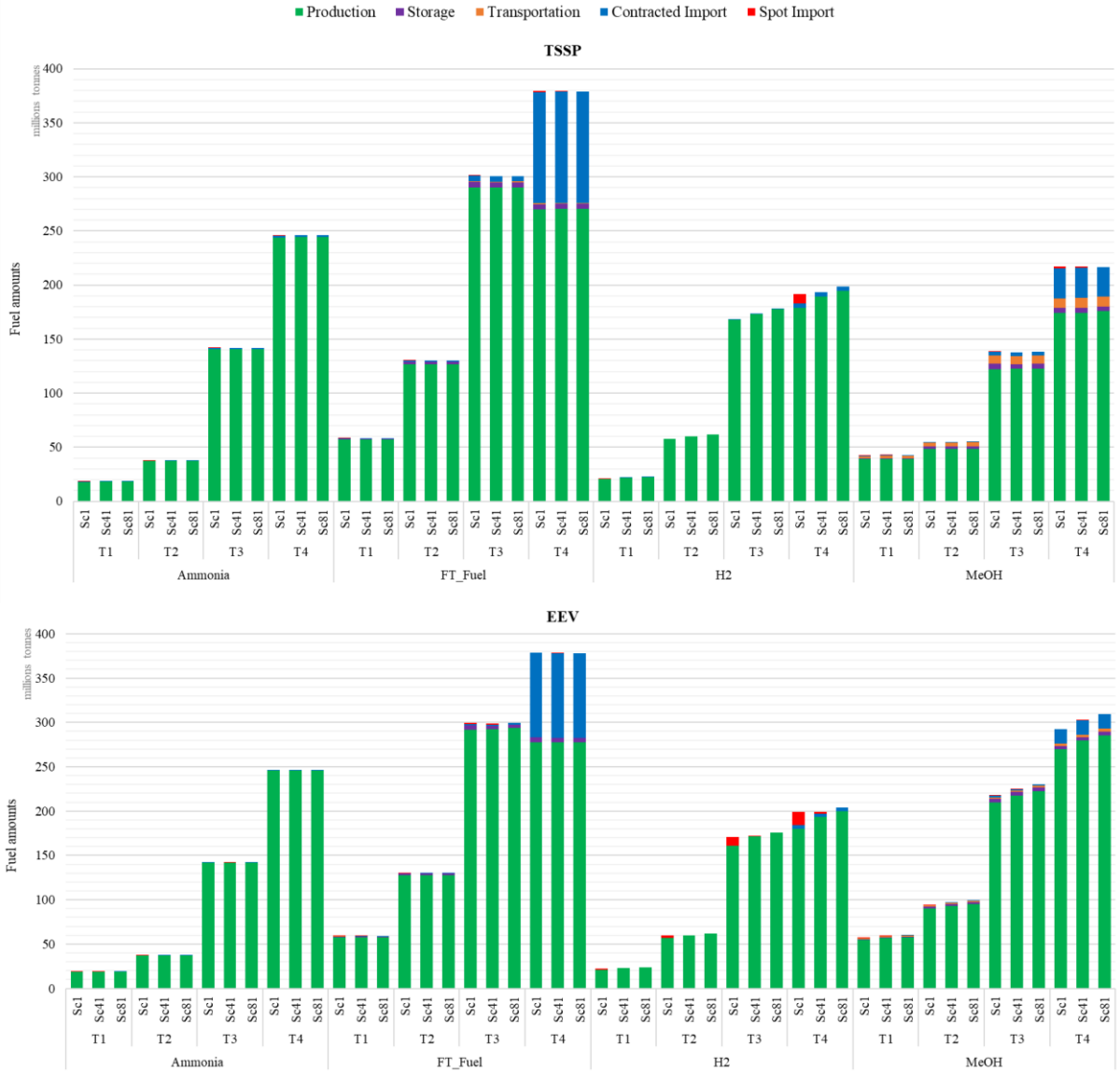


Figure 7-11: Demand fulfillment for TSSP and EEV solutions

Figure 7-12 shows the deviations of Sc1 and Sc81 relative to the baseline Sc41 across time and fuels. Aggregated over fuels (panel a), Sc1 leads to negative deviations in both approaches, with the contraction becoming stronger over time and significantly larger under EEV, while TSSP exhibits a more moderate decline and partial recovery in T4. Under Sc81, deviations turn positive, increasing markedly from T2 onward, again with substantially stronger expansion under EEV compared to the smoother and more stabilized increase under TSSP. Aggregated over time (panel b), the largest scenario sensitivities are observed for MeOH and H_2,

which show strong negative deviations under Sc1 and strong positive deviations under Sc81, particularly in EEV, whereas NH_3 remains comparatively stable and FT-fuel shows moderate changes. Overall, the deterministic EEV approach amplifies scenario-induced fluctuations, while TSSP dampens these deviations, indicating a more balanced and resilient response to uncertainty.

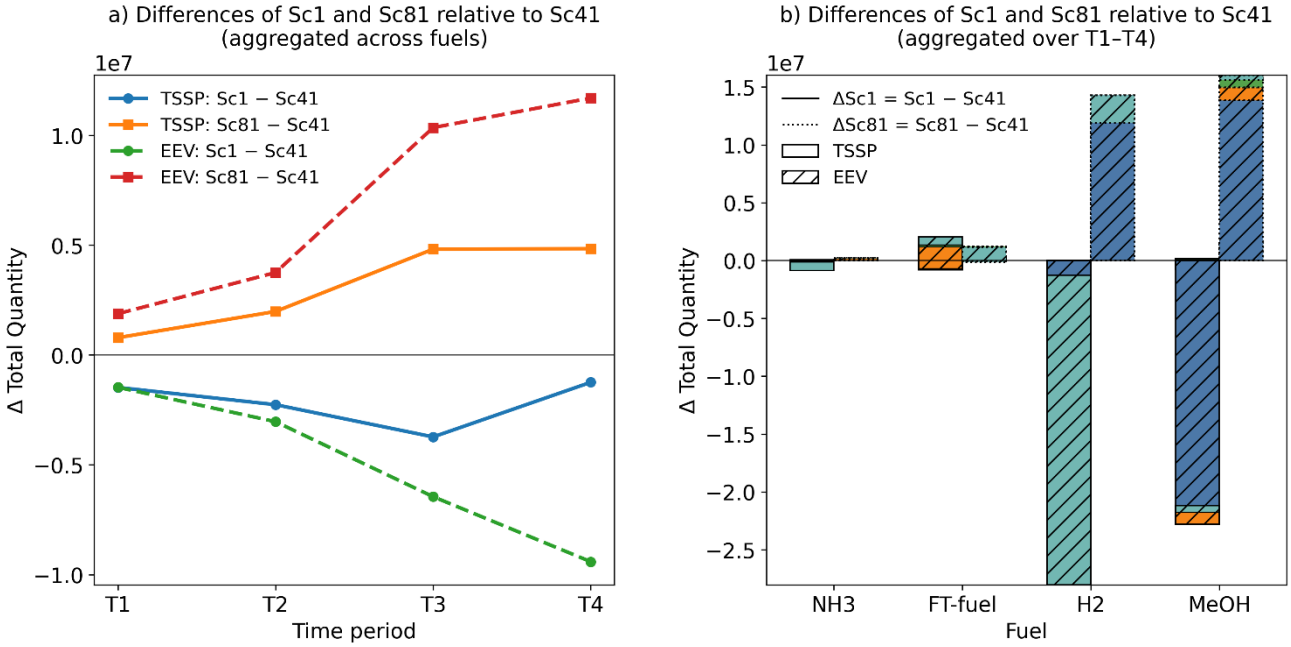


Figure 7-12: Differences of Sc1 and Sc81 relative to Sc41 under TSSP and EEV, shown (a) over time (aggregated across fuels) and (b) by fuel (aggregated over T1–T4)

7.5.3 Discussion, summary, and limitations of the study

One of the central insights from this research is that renewable energy investments dominate investments for fuel production technologies, particularly in T1 and T3, where large-scale solar photovoltaic and wind power capacities are installed. The spike in investments in T3 aligns with the assumed increase in fuel demand, reflecting the strong need to meet final decarbonization milestones before 2050. Interestingly, in T4, RES investment drops sharply due to limited available resources, while contracted imports surge. This suggests that after substantial domestic capacity expansion, the system shifts to partly relying on external sources of renewable fuels. This late reliance on imports reflects both the constraints on domestic feedstocks and the possibility that some countries outside the EU+UK could offer more cost-competitive, low-carbon fuels by T4. Production investments follow a similar pattern, high in early periods to establish domestic industrial capacity, then tapering in T4. The steady O&M costs for both renewable and production technologies reflect a gradual shift toward cleaner, albeit more cap-

ital-intensive, renewable fuels. In contrast, transportation and storage costs remain relatively low, partly because pipeline expansion and storage deployment are overshadowed by the heavy investment in fuel production and renewable electricity generation. This result suggests that, at a pan-European level, leveraging existing infrastructure or making only marginal additions may suffice when production sites and consumption centers are better aligned, or when imports from outside Europe fill local shortfalls.

A more granular look at the installed capacities reveals regional specialization, which reflects regional resource abundance. Southern countries such as Spain and Italy show strong growth in PV due to favorable solar irradiance, while northern and western countries, like Germany and the UK, emerge as leaders in wind power. France stands out as having the fastest growth in both solar and wind. Meanwhile, Austria and Bulgaria leverage abundant biomass for BtL and PBtL technology, reflecting the importance of local resource endowment in shaping technology portfolios. For fuel production technologies, Germany and Spain lead in the number of PtL facilities and electrolyzers, capitalizing on their strong renewable capacity expansions. France and Poland prioritize NH_3 production, supported by ASUs. This geographic dispersion of capacity suggests that, while an EU-wide decarbonization policy framework can guide investments, local resource conditions, be they solar irradiance, wind availability, or biomass potential, ultimately shape the specific technology mix.

The difference between the highest-cost scenario and the lowest-cost scenario is around 6%. This narrow cost band indicates a relatively robust design; even under unfavorable capacity factor realizations for renewables, the system does not incur drastically higher costs. A large contributor to cost variability is biomass, which provides flexibility in scenarios with low availability of electricity. Spot imports also exhibit high volatility, particularly in T4 under the worst-case scenarios, underscoring how uncertain future energy market conditions (e.g., global LNG prices, import policies) can influence planning. However, the SC demonstrates an ability to absorb these fluctuations through technology diversification and contractual arrangements, particularly if decision-makers adopt a multi-stage strategy that continuously adapts to updated forecasts.

Two important sensitivity analyses further illuminate the model's behavior. Varying the ratio of spot import prices (3×, 5×, and 10× contracted import costs) shows that, as spot imports become more expensive, the system invests more in domestic production and feedstocks to hedge against expensive spot procurements. Interestingly, the total cost does not escalate dra-

matically, suggesting that the model finds cost-effective pathways to mitigate reliance on high-priced spot markets, whether by ramping up domestic capacity or locking in more long-term contracts. Lowering the permissible share of contracted imports to 10% forces greater domestic production of both renewable power and fuels, leading to increased investments and a slight rise in total system cost. Conversely, increasing the import share to 30% yields notable cost benefits, while pushing it further to 50% brings only marginal savings. While total costs decline moderately at higher import shares, heavy reliance on external sources might introduce geopolitical and supply-security concerns, an aspect policymakers must weigh against purely economic criteria.

The performance evaluation shows that stochastic programming yields clear advantages over deterministic approaches, with a VSS of 3.4% and an EVPI of 4.5% highlighting the value of modeling uncertainty. A higher VSS indicates greater benefits from stochastic programming, while EVPI measures the theoretical value of perfect information and benchmarks sensitivity to uncertainty. What matters is that VSS is positive, showing that the stochastic solution outperforms deterministic ones, while EVPI highlights the importance of uncertainty in long-term planning. While temporal cost patterns are broadly similar, absolute levels diverge in later periods, reflecting the role of uncertainty resolution and capacity expansion. Demand fulfillment further indicates that production remains central, but reliance on imports and storage grows under stress, particularly for FT-fuel and MeOH. Overall, these results emphasize the importance of stochastic modeling for cost efficiency, flexibility, and system resilience.

Despite its comprehensive nature, the model has some limitations. While the capacity factor of renewables is captured through a normal distribution with parameters derived from historical data, real-world variability can exhibit non-Gaussian behavior, correlated events, and tail risks that might not be fully encapsulated in this approach. In addition, intra-seasonal fluctuations are not addressed, as we rely on seasonal averages; capturing these dynamics would require a finer temporal resolution, which could be explored in future work. Additionally, the decision-dependent nature of uncertainty, where the timing and scale of investments can affect future market conditions, remains a complex modeling challenge (Birge, 1982).

Also, generally, TSSP faces limitations in practical applications despite its advantages. Handling multiple sources of uncertainty, such as wind and solar variability, load demands, and emission factors, requires extensive, high-quality historical data, which is often lacking. This can lead to imprecise or unreliable models. Moreover, stochastic methods sometimes un-

derrepresent the complexities of parameters, resulting in only marginal cost benefits compared to deterministic models. The issue of decision-dependent uncertainty, where current decisions influence future probability distributions, further complicates scenario generation. Consequently, capacity planning for renewable energies involves complex interdependencies and evolving uncertainties, which could benefit from methodological extensions such as multi-stage stochastic programming, robust optimization, or stochastic dynamic programming

The study focuses on fuels and associated infrastructure, but other sectors (e.g., industrial and building) could compete for the same resources and infrastructure pathways. Moreover, potential synergies with battery storage, carbon capture and utilization, or sector coupling strategies (power-to-heat, power-to-gas) could yield different results if included. Multi-decade optimization relies on technology cost forecasts and resource availability estimates that may evolve with policy changes, R&D breakthroughs, or unexpected climate events. Improving the accuracy of future cost trajectories, or integrating dynamic learning curves, may alter investment timing and capacity choices.

7.6 Conclusion

This study addresses the problem of designing a renewable fuel SC under uncertain capacity factors for solar and wind power. By employing a TSSP framework, the model determines long-term infrastructure investments before uncertainties are realized, and then adjusts operational decisions accordingly. We solved a full factorial set of three distinct capacity factor levels for solar and wind across four time periods, 81 scenarios in total, demonstrating the model's practical tractability and robust performance.

The results highlight the significant upfront capital expenditure required for large-scale renewable energy installations, particularly in solar- and wind-rich regions, and illustrate how strategic reliance on imports can become more cost-effective at later planning stages. Sensitivity analyses reveal that our stochastic model presents solutions that remain relatively robust even under less favorable capacity factor scenarios, with only a modest cost difference across best and worst cases. Moreover, local resource conditions significantly influence where and how renewable and production capacities are deployed, indicating the importance of regional specialization in an EU-wide decarbonization strategy.

The increasing penetration of solar and wind power in renewable fuel production brings both opportunities and challenges. On the one hand, incorporating uncertainty into SC design can enhance overall flexibility by accounting for fluctuating capacity factors. This approach

can minimize the risk of inadequate capacity while allowing the system to adapt to real-world variability. However, such flexibility might lead to higher underutilization rates and, consequently, additional costs of robustness which only pay-off under adverse scenarios. Furthermore, we are able to show in our case study that operational complexity imposed by renewable energy's intermittent output necessitates a transition from deterministic optimization to uncertainty-based models, ensuring a more robust approach to managing power systems.

We acknowledge that this study has certain limitations. Future research should investigate more advanced representations of uncertainty, including correlated demand and supply shocks, and extend the framework to a multi-stage stochastic programming approach to capture evolving uncertainties and additional sources such as demand dynamics and emerging technology performance. In doing so, it is recommended to consider multiple uncertainties simultaneously to uncover potential synergies and include risk considerations, as well as investigate approaches like robust optimization. Storage systems (e.g., batteries) could also be modeled more explicitly, including their cost implications. Strengthening the link between local conditions, such as public acceptance of large-scale renewables, availability of storage sites, and pipeline routing, future SC design could further refine investment insights. Ultimately, these methodological extensions will inform cost-effective, low-carbon strategies that remain resilient under uncertain renewable energy availability and shifting market conditions for achieving ambitious decarbonization targets.

7.7 Supplementary Materials

All model input data and complete computational results supporting this study are provided in the supplementary materials available at https://doi.org/10.5281/zenodo.18721691

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7.9 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.

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Chapter 8

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

Authors: Mina Farajiamiri, Jörn-Christian Meyer, Grit Walther

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

Keywords: Decision support systems, Multi-Stage Stochastic Programming, Renewable Fuels, Supply Chain Network Design, Mixed Integer Linear Programming, Demand Uncertainty

Abstract

Decarbonizing the transportation sector requires large-scale deployment of renewable fuels and the development of robust supply chain infrastructures capable of coping with long-term uncertainty. Strategic planning of renewable fuel supply chains is particularly challenging due to evolving demand trajectories, capital-intensive infrastructure, and the need to coordinate renewable electricity resources with fuel production technologies. This study develops a multistage stochastic mixed-integer linear programming framework to support long-term planning of renewable fuel supply chain networks under demand uncertainty. The model captures sequential decision-making over multiple planning stages, allowing infrastructure investments and operational decisions to adapt as new information about future demand becomes available.

To represent uncertainty realistically while maintaining computational tractability, a data-driven demand scenario framework is implemented, combining autoregressive demand modeling with scenario reduction techniques. 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.

Results demonstrate the substantial economic value of adaptive planning. Compared with deterministic approaches, the multistage framework achieves a Relative Value of the Multistage Stochastic Solution of 19.4% and an Expected Value of Perfect Information of 14.2%. Further-

more, the analysis demonstrates how the proposed model effectively balances strategic and tactical decisions under demand uncertainty. By incorporating sequential information updates, the framework reveals how technology costs, regional resource availability, and import strategies interact in shaping optimal infrastructure and supply chain planning.

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 model provides a robust decision-support tool for cost-efficient and adaptive planning of renewable fuel supply chains.

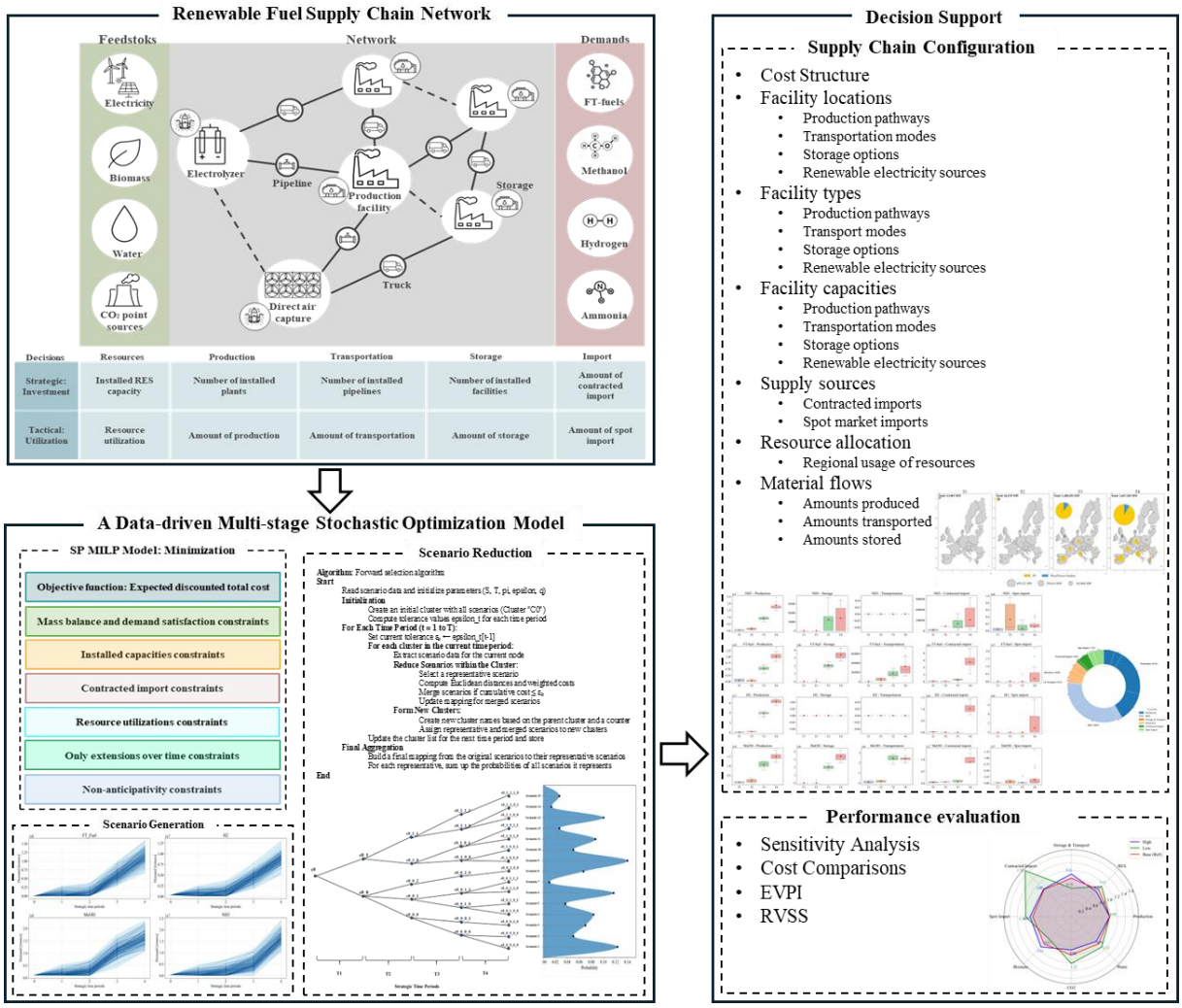


Figure 8-1: Graphical Abstract

8.1 Introduction

The transportation sector is a major emitter of greenhouse gases 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, 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 (RFSC) 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 (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 supply chain 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 & Huang, 2018; Zarei et al., 2022). Deter-

ministic 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 & 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. 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 consideration 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.

To address this need, we propose an MSSP model for the design of an RFSC, incorporating demand uncertainty. Our approach links strategic and tactical decisions across multiple periods, enabling adaptive planning under evolving uncertainty. Scenarios are generated using an autoregressive demand process and reduced with a forward selection heuristic to ensure com-

putational tractability. The framework is applied to an EU-wide case study, revealing how sequential demand information shapes technology choices, infrastructure expansion, and import strategies. 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, products, technologies, storage options, 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.
- Application of the framework to a long-term European case study (2021–2060), quantifying the economic value of adaptive planning and providing insights into renewable fuel infrastructure deployment, import strategies, and resource allocation.

By addressing these limitations, this study advances the literature on stochastic energy system planning and RFSC, providing a more realistic representation of long-term adaptive decision-making under demand uncertainty. 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.

8.2 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.

8.2.1 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 & 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 (Čuček et al., 2014; Malladi & Sowlati, 2018; Yue et al., 2014; 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 analyses 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 & Nguyen, 2020; Albrecht et al., 2017; Quarton & Samsatli, 2020).

Temporal and structural complexity further shape RFSCs. Some studies do consider seasonal variability by incorporating renewable energy storage (Fattahi & Govindan, 2018; Liu et al., 2017; Quddus et al., 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 (Lara et al., 2018; Quarton & Samsatli, 2020). Reflecting a growing awareness of dynamic conditions, recent research has moved toward multi-period frameworks (Čuček et al., 2014; Hombach et al., 2016; Hombach & Walther, 2015; Lim & Ouyang, 2016; Samsatli & Samsatli, 2018; Wolff et al., 2023; Xie et al., 2014). 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 (Vos et al., 2020; Nichol et al., 2023; Shin et al., 2025).

8.2.2 Approaches to uncertainty in RFSCs

Uncertainty is a defining characteristic of RFSCs. Key uncertainties addressed in the literature include feedstock supply (Castillo-Villar et al., 2017; Guo et al., 2022; Huang et al., 2014; Memişoğlu & Üster, 2021; Poudel et al., 2018), fuel demand (Asadi et al., 2018; Gonela et al., 2015; Kalhor et al., 2022; Osmani & Zhang, 2013, 2017; Xie & Huang, 2018), and SC costs and prices (Cobuloglu & Büyüktahtakın, 2017; Gonela et al., 2015; Osmani & Zhang, 2014; Zhang & Osmani, 2015). Additionally, some research includes disruption risks in biofuel SC planning, incorporating the probability of failures in facilities or transportation (Marufuzzaman et al., 2014; Marufuzzaman & Ekşioğlu, 2017; Poudel et al., 2016). 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 & Walther, 2023). Deep uncertainty, where only parameter bounds are known, is addressed by robust optimization (Bairamzadeh et al., 2018; Delkhosh & Sadjadi, 2020; Ghelichi, Tajik, et al., 2018; Hombach et al., 2018; Kalhor et al., 2022). Randomness, based on reliable historical data, allows the use of stochastic programming methods such as chance-constrained, two-stage, or multi-stage models (Aboytes-Ojeda et al., 2019; Li et al., 2022; Memişoğlu & Üster, 2021; O'Neill et al., 2022; Zarei 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 (Gonela et al., 2015; Li & Hu, 2014; Osmani & Zhang, 2013; 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., 2017, 2018). 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 & Louveaux (2011) 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 (Fattahi et al., 2017, 2018; Fattahi & Govindan, 2018; Nickel et al., 2012; Xie & Huang, 2018).

Table 8-1 summarizes studies applying MSSP to complex planning problems under uncertainty across domains such as biofuel supply chains, manufacturing networks, water management, reverse logistics, and energy systems. 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. Building on the advances summarized in Table 8-1, our study positions MSSP as a robust framework for explicitly modeling the dynamic, uncertain nature of RFSCs, enabling more realistic long-term planning.

8.2.3 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 address the limitations identified in the literature, this study develops an MSSP framework tailored to RFSCs. First, it addresses the overreliance on deterministic, two-stage, or ro-

bust 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 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.

Table 8-1: Summary of Related MSSP Studies

(CP = Capacity Planning, WRM = Water Resources Management; MP/SP = Multi-/Single-Product; MR/SR/MC = Multi-/Single-Resource, Multi-Commodity; ST = Scenario Tree, SR = Scenario Reduction)

Ref	General Problem	Uncertainty parameter	Objective functions	Resource/ Product	Time resolution	Scenario gen/red	Method/ Solution	Application
Zarei et al. (2022)	SC	Biomass supply & demand	Min cost	MP	3 stages, 5 years	Scenred2	-	Biofuel
Xie & Huang (2018)	SC	Biomass supply	Max profit	SR	-	-	Nested decomposition	Biofuel
Fattahi et al. (2018)	SC	Price-dependent demand	Max profit, min cost	MP	4 stages, 3 periods	LHS	Benders decomposition	Global
Zahiri et al. (2018)	SC	Blood demand	Min cost	SR	-	Moment matching	Self-adaptive algorithm	Blood
Fattahi et al. (2017)	SC	Demand, capacity	Max responsiveness	MP	4 stages, 3 periods	Mitigation strategies	Contingency strategies	Global
Felfel et al. (2015)	SC	Demand	Max profit	MP	4 stages	-	-	Global
Nickel et al. (2012)	SC	Demand, interest rate	Max benefit	MC	3 stages	ST	-	Global
Goh et al. (2007)	SC	Supply, exchange rate	Max profit	MP	-	SR	Regularization	Global

Pimentel et al. (2013)	CP	Demand, capacity	Min cost	SP	3 stages	ST	Lagrangian heuristic	Mining
Huang & Ahmed (2009)	CP	Investment cost	Max return	MR	2 to 5 stages, 4-6 months	ST	Sequential programming	Semiconductor
Ahmed et al. (2003)	CP	Expansion cost	Min cost	MR	2 to 5 stages	ST	Branch and bound	Heavy process, electric utility
Zhang et al. (2019)	WRM	Runoff	Max benefit	SR	4 stages, 3 seasons	Deviation method	Interval-based programming	Water
Zhou et al. (2013)	WRM	Interactions	Max benefit	SR	3 stages	Factorial analysis	Multi-parameter interactions, Factorial MSSP	Water
Li et al. (2006)	WRM	Demand	Max benefit	SR	3 stages	Interval parameters	Interval-based programming	Water
Wang & Neufville (2004)	Physical system design	Project interdependency	Max flexibility	SR	3 stages, decade	Options analysis	-	Water
Azizi & Hu (2021)	Reverse logistics network design & lot sizing	Return quantity	Min cost	MP	3 stages, month	Moment matching, SR	-	Reverse logistics
Hu & Hu (2018)	Lot-sizing & scheduling	Demand	Min cost	MP	Half a year, week, or month	Moment matching, SR	-	Automotive
Li et al. (2022)	Production planning	Demand & yield	Min cost	SR	4 stages	-	Hybrid model with heuristic	Bioethanol
Hafiz et al. (2019)	Energy management & storage sizing	Demand, solar generation	Min cost	SR	One-day cycle, 1-minute resolution	Decomposition	-	PV & storage
Wang et al. (2023)	Island power systems	Carbon price	Min cost	MR	6 stages, 4 years	Binomial tree	Stochastic Nested Decomposition	RES, storage, transmission
Kim & Lee (2023)	Microgrid design	Demand growth, cost	Max performance	MR	4 stages, decade (hourly decisions)	Reinforcement learning	DQN, multi-scale SP	Power-to-hydrogen, RES, storage
Hu et al. (2019)	Relief distribution	Road capacity, vehicle availability	Min cost	MR	3 stages, daily resolution	-	Progressive hedging	Disaster-affected areas
Herzog et al. (2007)	Asset & liability management	Asset return, liability	Max return	MR	quarterly frequency	ST	Sequential programming	Asset & liability management

8.3 Methodology

This section describes the underlying problem, planning decisions, the MSSP framework for modeling uncertainty, and the scenario construction approach.

8.3.1 Problem setting

RFSCs differ from conventional SCs due to several structural and operational characteristics. Production depends on capital-intensive, technology-specific conversion processes linking renewable electricity and feedstocks to fuel outputs. RFSCs integrate multiple feedstocks, fuels, and production pathways, alongside diverse storage and transportation technologies with different costs, efficiencies, and capacity requirements. Spatial heterogeneity further increases complexity, as resource availability, infrastructure capacity, and demand vary across regions. Temporal aspects are also critical. Infrastructure investments are long-lived and largely irreversible, while renewable resource availability is seasonal. In addition, fuels can be sourced domestically or through international import strategies, including long-term contracts and spot procurement. Finally, demand evolves under significant uncertainty, requiring adaptive decisions over multiple planning stages. These characteristics motivate the use of a MSSP framework.

We model an SC to produce renewable fuels from sustainable resources, as shown in Figure 8-2. 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.

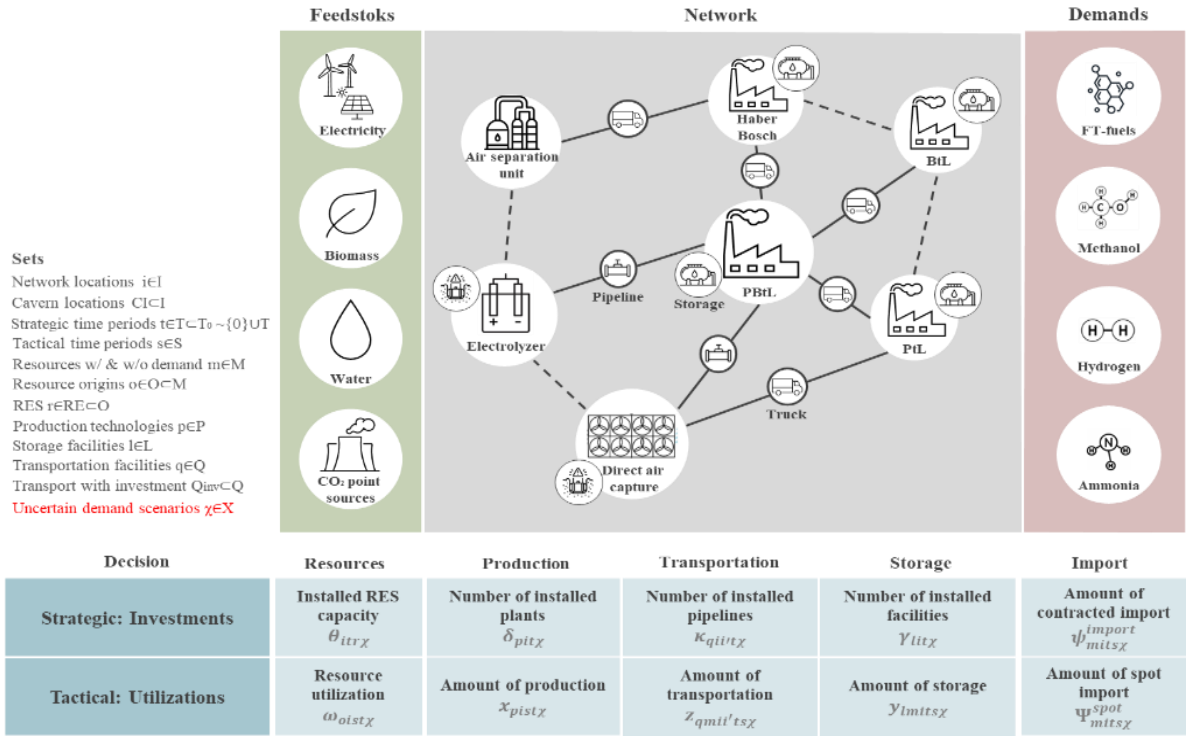
Multiple production technologies and pathways ($p \in P$) that transform resources are evaluated, including hydrogen (H_2) production through Alkaline (AEL) and Proton Exchange Membrane (PEM) electrolysis. FT-fuels and MeOH are produced via three main pathways: Biomass-to-Liquid (BtL), Power-to-Liquid (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. The research assumes that these pathways will remain in use throughout the time horizon considered. 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. Seasonal periods follow cyclical orders, meaning each season's inventory balance links to the preceding one.

As shown in Figure 8-2 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.



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 $\kappa_{qii'l\chi}$	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 $\psi^{spot}_{mits\chi}$

Figure 8-2: RFSC with sets and decision variables

8.3.2 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.

Figure 8-3 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.

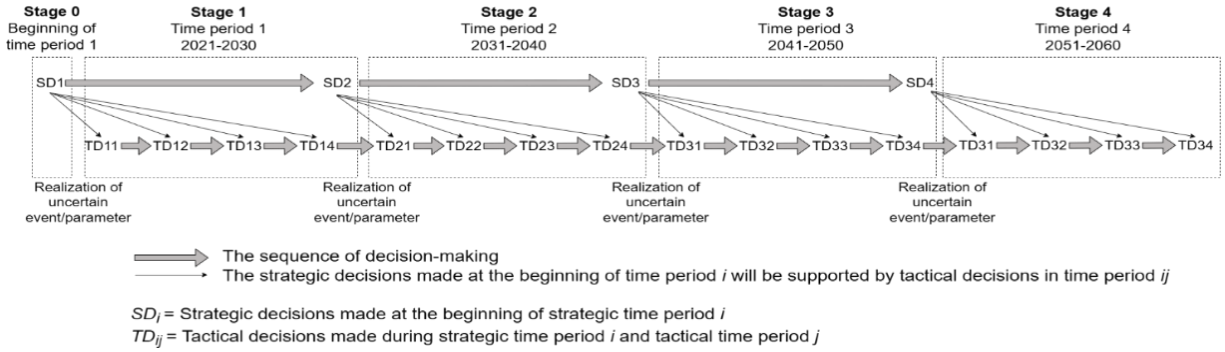


Figure 8-3: Sequence of decision-making, our own illustration for our case study, adjusted based on (Xie & Huang, 2018)

According to Dupačová (1995), 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.

Notation:

System parameters - Deterministic	
$\boldsymbol{\Theta_{ir}}$	Max allowable installation capacity for renewable electricity source r in region i $[MW]$
$\boldsymbol{\vartheta_{isr}}$	Capacity factor of renewable electricity source r in region i and season s [1]
$\boldsymbol{\upsilon_{mt}}$	Max amount of allowed resource m imported in period t
$\boldsymbol{\alpha_{mp}}$	Rate of conversion of resource m by production technology p $[tonnes/tonnes]$, $[MWh/tonnes]$
$\boldsymbol{\beta_{om}}$	1, if resource m is available from origin o; 0 otherwise
$\boldsymbol{K_p^{prod}}$	Production capacity of technology p $[tonnes/hour]$
$\boldsymbol{K_l^{stor}}$	Storage capacity of technology l per season $[tonnes/season]$
$\boldsymbol{K_q^{tran}}$	Transport capacity of technology q $[tonnes/hour]$
$\boldsymbol{A_{lm}}$	Resource m storable in technology l
$\boldsymbol{B_{qm}}$	Resources m transportable by technology q
$\boldsymbol{d_{ii'}}$	Distance between region i , i' $[km]$
$\boldsymbol{B_{ii'}^{truck}}$	Region pairs (i, i') that allow transportation via trucks
$\boldsymbol{B_{ii'}^{pipe}}$	Region pairs (i, i') that allow transportation via pipelines
$\boldsymbol{n}$	Years in a strategic time period
$\boldsymbol{H}$	Hours per season
$\boldsymbol{H'}$	Operating hours per season
Cost-related parameters - Deterministic	
$\boldsymbol{\tau}$	Rate of discounting $[1/year]$
$\boldsymbol{\zeta_t^{sp}}$	Discount factor associated with strategic period t [1]
$\boldsymbol{\zeta_t^{yp}}$	Annual discount factor for period t [1]
$\boldsymbol{f_p^{prod}}$	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 [€]
$v_q^{trans,dis}$	Distance-related unit transport costs of technology q [€/$tonne.km$]
v_q^{tran}	Unit transport costs of technology q [€/$tonne$]
v_{oit}	Unit purchasing costs of resource origin o in region i in period t, [€/$tonne$]
v_{mt}^{import}	Price of contracted import of product m in period t [€/$tonne$]
v_{mt}^{spot}	Price of spot import of product m in period t [€/$tonne$]
Decision variables - Strategic	
$\theta_{itr\chi}$	Installed capacity of renewable electricity source r in region i up to period t for scenario χ [MW]
$\delta_{pit\chi}$	Number of production plants p installed in region i up to period t for scenario χ
$\gamma_{lit\chi}$	Number of storage units of storage technology l installed in region i up to period t for scenario χ
$\kappa_{qii't\chi}$	Number of transportation infrastructures $q \in Q_{inv}$ installed between region i and i' up to period t for scenario χ
$\psi_{mit\chi}^{import}$	Amount contracted import material m to region i in period t during each season for scenario χ [$tonnes/season$]
Decision variables - Tactical	
$\omega_{oist\chi}$	Utilization of resource origin o in region i during period t and season s under scenario χ [$tonnes/season$], [$MWh/season$]
$x_{pist\chi}$	Production rate of production pathways p in region i in period t during season s under scenario χ [$tonnes/season$]
$y_{lmits\chi}$	Amount of resource stored with storage technology l in region i in period t during season s under scenario χ [$tonnes/season$]
$z_{qmii'ts\chi}$	Amount of resource m transported from region i to i' using transport technology q in period t during season s under scenario χ [$tonnes/season$]
$\Psi_{mits\chi}^{spot}$	Amount of spot import of material m in region i in period t during season s under scenario χ [$tonnes/season$]

8.3.2.1 Objective function and cost components

The objective function minimizes the expected net present value of total system costs by selecting variables such that discounted costs are reduced 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 Equation (8.1). Equation (8.2) denotes the discounting factor for strategic decisions, and Equation (8.3) shows the discounting factor for tactical decisions. 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 ($v_{mt}^{import}\psi_{mit\chi}^{import}$). Tactical decisions cover variable transportation (($v_q^{trans,dis} d_{ii'} + v_q^{tran}$)$z_{qmii'ts\chi}$), resource procurement ($\omega_{oist\chi}v_{oit}$), and spot imports ($v_{mt}^{spot}\Psi_{mits\chi}^{spot}$). The objective function is then obtained by aggregating these cost components across all scenarios, weighted by their respective probabilities.

$$
\begin{aligned}
Min\ ETC = \sum_{t\in T}\sum_{\chi\in X} \Pr(\chi) \Bigg(& \zeta_t^{sp} \Bigg(\sum_{i\in I}\sum_{p\in P} f_p^{prod}\left(\delta_{pit\chi} - \delta_{pi(t-1)\chi}\right) + \sum_{i\in I}\sum_{l\in L} f_l^{stor}\left(\gamma_{lit\chi} - \gamma_{li(t-1)\chi}\right) \\
& + \sum_{i\in I}\sum_{i'\in I|i'\neq i}\sum_{q\in Q_{inv}} f_q^{trans} d_{ii'}\left(\kappa_{qii't\chi} - \kappa_{qii'(t-1)\chi}\right) + \sum_{i\in I}\sum_{r\in RE} f_r^{RE}\left(\theta_{itr\chi} - \theta_{i(t-1)r\chi}\right) \Bigg) \\
& + \zeta_t^{yp} \Bigg(\sum_{i\in I}\sum_{p\in P} c_p^{prod}\delta_{pit\chi} + \sum_{i\in I}\sum_{l\in L} c_l^{stor}\gamma_{lit\chi} + \sum_{i\in I}\sum_{i'\in I|i'\neq i}\sum_{q\in Q} c_q^{trans} d_{ii'}\kappa_{qii't\chi} + \sum_{i\in I}\sum_{r\in RE} c_r^{RE}\theta_{itr\chi} \\
& + \sum_{m\in M}\sum_{i\in I}\sum_{s\in S}\left(v_{mt}^{import}\psi_{mits\chi}^{import}\right) + \sum_{o\in O\setminus RE}\sum_{i\in I}\sum_{s\in S}\left(\omega_{oist\chi}v_{oit}\right) \\
& + \sum_{s\in S}\sum_{i\in I}\sum_{i'\in I|i'\neq i}\sum_{q\in Q}\sum_{m\in M}\left(v_q^{trans,dis} d_{ii'} + v_q^{tran}\right) z_{qmii'ts\chi} + \sum_{m\in M}\sum_{i\in I}\left(v_{mt}^{spot}\Psi_{mits\chi}^{spot}\right) \Bigg) \Bigg)
\end{aligned}
\tag{8.1}
$$

$$\zeta_t^{sp} = (1+\tau)^{-n(t-1)}, \qquad t \in T \tag{8.2}$$

$$\zeta_t^{yp} = \left(\sum_{i=1}^{n}(1+\tau)^{1-i}\right)\zeta_t^{sp}, \qquad t \in T \tag{8.3}$$

8.3.2.2 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 (Equation (8.4)). Contracted imports are limited by permitted import shares (Equation (8.5)). The output of each production technology cannot exceed its installed capacity (Equation (8.6)). Storage levels are restricted by installed capacity and compatibility with designated storage types (e.g., caverns), ensuring that only suitable locations are used (Equation (8.7)). 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 (Equations (8.8–9)). Resource use is further bounded by regional availability of feedstocks and inputs such as biomass, carbon, and water (Equation (8.10)). The use of renewable electricity from wind and solar is limited by installed capacity, seasonal capacity factors, and

the number of hours per season, while regional maximum installable capacities further restrict the installation of onshore and offshore facilities (Equations (8.11–12)). 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 (Equations (8.13–16)). Equations (8.17-18) denote the type of variables.

$$\sum_{O\in O}\beta_{om}\omega_{oits\chi} + \sum_{p\in P}\alpha_{mp}\, x_{pits\chi} + \sum_{L\in L|(l,m)\in A_{lm}}\left(y_{lmit(s-1)\chi} - y_{lmits\chi}\right) + \sum_{i'\in I}\sum_{q\in Q|(q,m)\in B_{qm}}\left(z_{qmi'its\chi} - z_{qmii'ts\chi}\right) + \psi^{import}_{mits\chi} + \Psi^{spot}_{mits\chi} \geq D_{mits\chi}, \quad m\in M, \quad i\in I, \quad t\in T, \quad s\in S, \quad \chi\in X \tag{8.4}$$

$$\sum_{s\in S}\sum_{i\in I}\psi^{import}_{mits\chi} \leq \upsilon_{mt}, \quad m\in M, \quad t\in T, \quad \chi\in X \tag{8.5}$$

$$x_{pits\chi} \leq H'\, K^{prod}_{p}\delta_{pit\chi}, \quad p\in P, \quad i\in I, \quad t\in T, \quad s\in S, \quad \chi\in X \tag{8.6}$$

$$y_{lmits\chi} \leq K^{stor}_{l}\gamma_{lit\chi}, \quad t\in T, \quad s\in S, \quad \chi\in X, \quad (l,m)\in A_{lm}, (l=caverns\rightarrow i\in CI)\wedge(l\neq caverns\rightarrow i\in I) \tag{8.7}$$

$$z_{qmii'ts\chi} \leq HK^{trans}_{q}\kappa_{qii't\chi}, \quad q\in Q_{inv}, \quad m\in M, \quad i,i'\in I, \quad t\in T, \quad s\in S, \quad \chi\in X \tag{8.8}$$

$$z_{qmii's\chi} = 0, \quad q\in Q, \quad m\in M, \quad i,i'\in I, \quad t\in T, \quad s\in S, \quad \chi\in X \mid B_{qm}=0\wedge i\neq i'\wedge B^{pipe}_{ii'}=0\ \wedge B^{truck}_{ii'}=0 \tag{8.9}$$

$$\omega_{oits\chi} \leq R_{oist}, \quad o\in O\setminus RE, \quad i\in I, \quad t\in T, \quad s\in S, \quad \chi\in X \tag{8.10}$$

$$\omega_{oits\chi} \leq H\theta_{itr\chi}\vartheta_{isr}, \quad o\in RE, \quad i\in I, \quad t\in T, \quad s\in S, \quad \chi\in X \tag{8.11}$$

$$\theta_{itr\chi} \leq \Theta_{ir}, \quad r\in RE, \quad i\in I, \quad t\in T, \quad \chi\in X \tag{8.12}$$

$$\theta_{i(t-1)r\chi} \leq \theta_{itr\chi}, \quad r\in RE, \quad i\in I, \quad t\in T_0, \quad \chi\in X \tag{8.13}$$

$$\delta_{pi(t-1)\chi} \leq \delta_{pit\chi}, \quad p\in P, \quad i\in I, \quad t\in T_0, \quad \chi\in X \tag{8.14}$$

$$\gamma_{li(t-1)\chi} \leq \gamma_{lit\chi}, \quad l\in L, \quad i\in I, \quad t\in T_0, \quad \chi\in X \tag{8.15}$$

$$\kappa_{qii'(t-1)\chi} \leq \kappa_{qii't\chi}, \quad q\in Q_{inv}, \quad i,i'\in I|i\neq i', \quad t\in T_0, \quad \chi\in X \tag{8.16}$$

$$\kappa_{qii't\chi}, \delta_{pit\chi}, \gamma_{lit\chi}\in \mathbb{N}_0, \quad q\in Q_{inv}, \quad p\in P, \quad l\in L, \quad i,i'\in I|\, i\neq i', \quad t\in T_0, \quad \chi\in X \tag{8.17}$$

$$z_{qmii'ts\chi},\ x_{pist\chi},\ y_{lmits\chi},\ \omega_{oist\chi},\ \Psi^{spot}_{mits\chi},\ \theta_{itr\chi},\ \psi^{import}_{mits\chi} \geq 0, \quad q\in Q, \quad p\in P, \quad l\in L, \quad m\in M, \quad o\in O, \quad i,i'\in I|i\neq i', \quad t\in T, \quad s\in S, \quad r\in RE, \quad \chi\in X \tag{8.18}$$

8.3.2.3 Non-anticipativity constraints

The equations (8.20-28) 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_t^{χ}. The uncertainty realization from the start of the planning horizon until/to the period t under scenario χ is represented by $\left(\xi_1^{\chi}, \xi_2^{\chi}, \dots, \xi_t^{\chi}\right)$. 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.

$$\theta_{itr\chi} = \theta_{itr\chi'}, \quad t = 1, \quad r \in RE, i \in I, \quad \chi', \chi \in \mathrm{X} \tag{8.19}$$

$$\theta_{itr\chi} = \theta_{itr\chi'}, \quad t \in T\backslash\{1\}, \quad r \in RE, i \in I, \chi', \chi \in \mathrm{X} : \left(\xi_1^{\chi}, \xi_2^{\chi}, \dots, \xi_{t-1}^{\chi}\right) = \left(\xi_1^{\chi'}, \xi_2^{\chi'}, \dots, \xi_{t-1}^{\chi'}\right) \tag{8.20}$$

$$\delta_{pit\chi} = \delta_{pit\chi'}, \quad t = 1, \quad p \in P, \quad i \in I, \quad \chi', \chi \in \mathrm{X} \tag{8.21}$$

$$\delta_{pit\chi} = \delta_{pit\chi'}, \quad t \in T\backslash\{1\}, \quad p \in P, \quad i \in I, \quad \chi', \chi \in \mathrm{X}: \left(\xi_1^{\chi}, \xi_2^{\chi}, \dots, \xi_{t-1}^{\chi}\right) = \left(\xi_1^{\chi'}, \xi_2^{\chi'}, \dots, \xi_{t-1}^{\chi'}\right) \tag{8.22}$$

$$\gamma_{lit\chi} = \gamma_{lit\chi'}, \quad t = 1, \quad l \in L, \quad i \in I, \quad \chi', \chi \in \mathrm{X} \tag{8.23}$$

$$\gamma_{lit\chi} = \gamma_{lit\chi'}, \quad t \in T\backslash\{1\}, \quad l \in L, \quad i \in I, \quad \chi', \chi \in \mathrm{X}: \left(\xi_1^{\chi}, \xi_2^{\chi}, \dots, \xi_{t-1}^{\chi}\right) = \left(\xi_1^{\chi'}, \xi_2^{\chi'}, \dots, \xi_{t-1}^{\chi'}\right) \tag{8.24}$$

$$\kappa_{qii't\chi} = \kappa_{qii't\chi'}, \quad t = 1, \quad q \in Q_{inv}, \quad i, i' \in I | i \neq i', \quad \chi', \chi \in \mathrm{X} \tag{8.25}$$

$$\kappa_{qii't\chi} = \kappa_{qii't\chi'}, \quad t \in T\backslash\{1\}, \quad q \in Q_{inv}, \quad i, i' \in I | i \neq i', \quad \chi', \chi \in \mathrm{X}: \left(\xi_1^{\chi}, \xi_2^{\chi}, \dots, \xi_{t-1}^{\chi}\right) = \left(\xi_1^{\chi'}, \xi_2^{\chi'}, \dots, \xi_{t-1}^{\chi'}\right) \tag{8.26}$$

$$\psi_{mits\chi}^{import} = \psi_{mits\chi'}^{import}, \quad t = 1, \quad m \in M, \quad i \in I, \quad \chi', \chi \in \mathrm{X}, \quad s \in S \tag{8.27}$$

$$\psi_{mits\chi}^{import} = \psi_{mits\chi'}^{import}, \quad t \in T\backslash\{1\}, \quad m \in M, \quad i \in I, \quad \chi', \chi \in \mathrm{X}: \left(\xi_1^{\chi}, \xi_2^{\chi}, \dots, \xi_{t-1}^{\chi}\right) = \left(\xi_1^{\chi'}, \xi_2^{\chi'}, \dots, \xi_{t-1}^{\chi'}\right), \quad s \in S \tag{8.28}$$

8.3.3 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 & 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 & 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.

8.3.3.1 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 (Dilaver & Hunt, 2021; Zimberg et al., 2019), 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 & 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 Equation (8.29):

$$D_{mt}^{\chi} = \mu_{mt} + \rho_m\left(D_{m,t-1}^{\chi} - \mu_{m,t-1}\right) + \epsilon_{mt}^{\chi} \tag{8.29}$$

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 (Fattahi et al., 2015; Govindan & Fattahi, 2017). 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.

8.3.3.2 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 (2003) and a study of TSSP models with stochastic resources by Römisch & Wets (2007) provides the basis for the methods for reducing scenarios discussed here. Based on the Monge-Kantorovich theory of mass transportation by Rachev & Rüschendorf (1998) these methods measure distances between probability distributions. As with the k-median problem, optimal scenario reduction problems are NP-hard. The forward and backward heuristic approaches developed by Dupacova et al. (2003) and further refined (Heitsch & Römisch, 2003, 2007) have demonstrated promising results in real-world applications.

The forward selection algorithm is used in this paper. Table 8-2 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.

Table 8-2: 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 $(S, T, \pi, \varepsilon, q)$

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: $\varepsilon_{tk} \leftarrow \varepsilon_t$

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 $\leq \varepsilon_{tk}$

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

8.4 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 Centre, 2019a), 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 Centre, 2019b, 2019c), and their capacity factors are based on the renewable ninjas database (Pfenninger & Staffell, 2016; Staffell & Pfenninger, 2016). H_2 production is assumed to rely on freshwater, with national freshwater potentials obtained from Eurostat (European Commission, 2022). Biomass prices follow the ENSPRESO reference scenario (European Commission Joint Research Centre, 2019a). Water prices are taken from the governance of European water services (EurEau, 2020; Varone & Ferrari, 2015). 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 (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 from the FVV (2021) and Vos et al. (2020). Three capacity levels with associated costs are modeled for most technologies based on the FVV (2021). The smallest capacity is available in period 1, larger ones in periods 2 and 4 to reflect technological progress in cost 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 from the FVV (2021).

We model two pipeline capacities for CO2 (Fasihi et al., 2019; McCollum & Ogden, 2006) and three capacities for H2 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 (IEA, 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) (Argus Media Group, 2024; REN21 Secretariat, 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 more than 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 based on the FVV (2021). 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 con-

tracted 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 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 tonne of spot imports is 3 times higher than contracted imports. All data parameters used in this case study, including their references, is available in the Supplementary Material.

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

Figure 8-4 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. Equation (8.29) ensures that each scenario reverts toward its fuel-specific mean path while allowing random shocks ϵ_{mt}^{χ}. 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 Equation (8.29), 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 and 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. Figure 8-5 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.

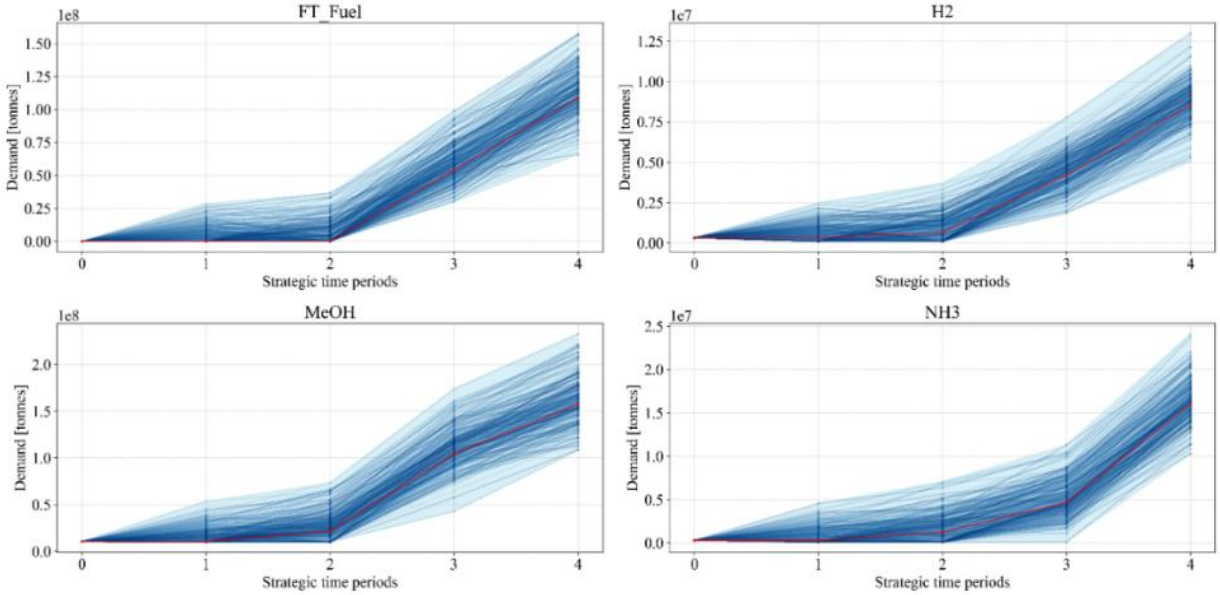


Figure 8-4: Demand scenario fan generated for the future demand of each fuel type

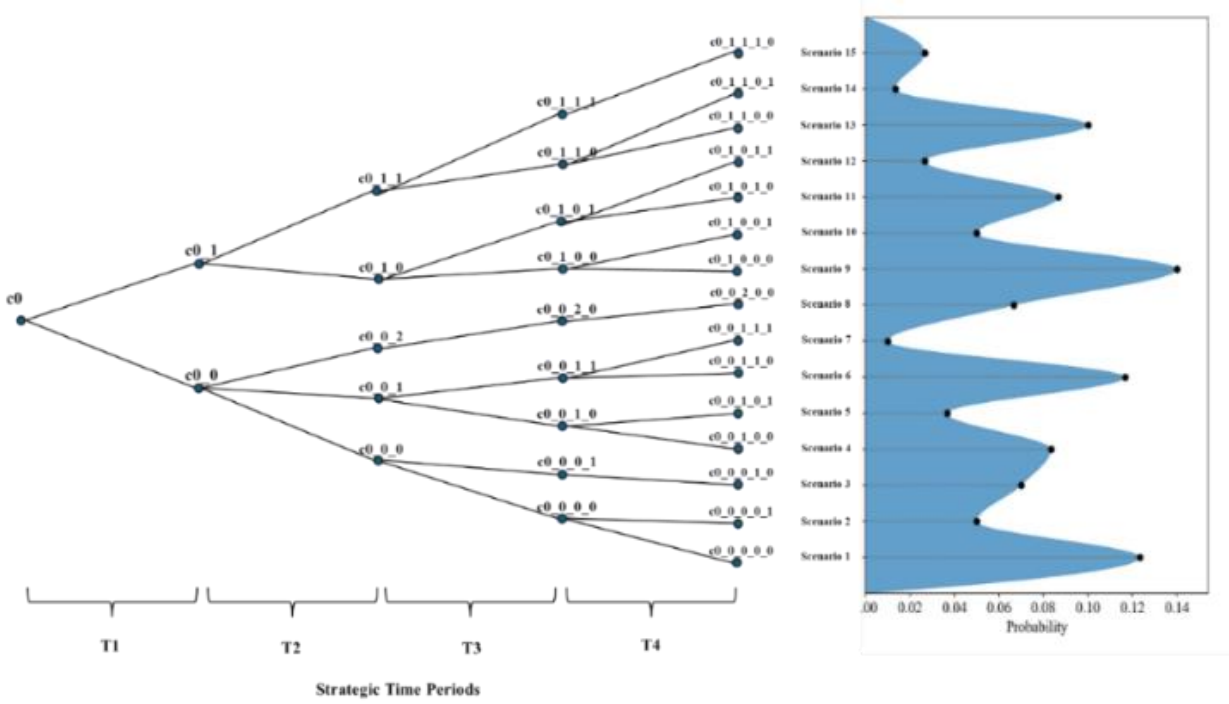


Figure 8-5: Scenario tree generated using our forward selection algorithm

8.5 Results and discussion

We evaluate the developed stochastic model and scenario generation procedure in this section. The developed stochastic program is solved for the real-world case study using Gurobi. The model is being solved using an AMD EPYC 9334 32-core Processor with 2700 MHz, 16 cores, 32 logical processors, and 250 GB of memory on a virtual machine. A maximum optimality gap of 0.05 is imposed to ensure timely results.

The optimal solution defines the overall supply chain 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. Figure 8-6 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 during these periods. This result pronounced escalation corresponds to the strong demand development in later stages (T3, T4) and the associated capacity expansions.

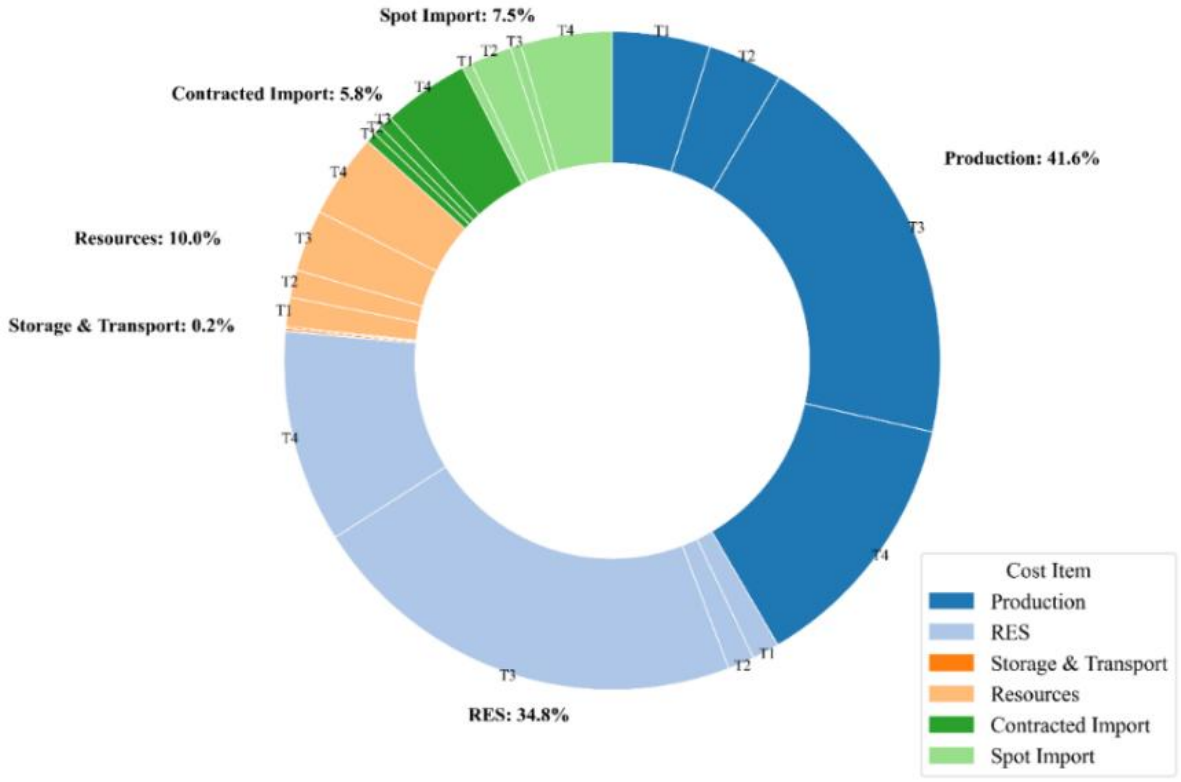


Figure 8-6: Expected cost structure

In Figure 8-7 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.

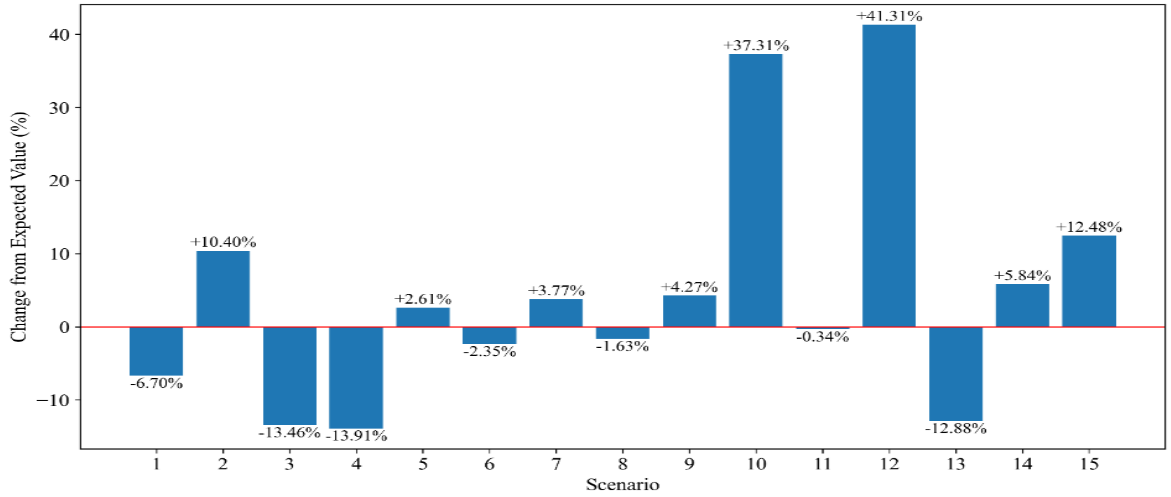


Figure 8-7: Percentage changes of the total cost of each scenario relative to the expected total costs

Figure 8-8 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.

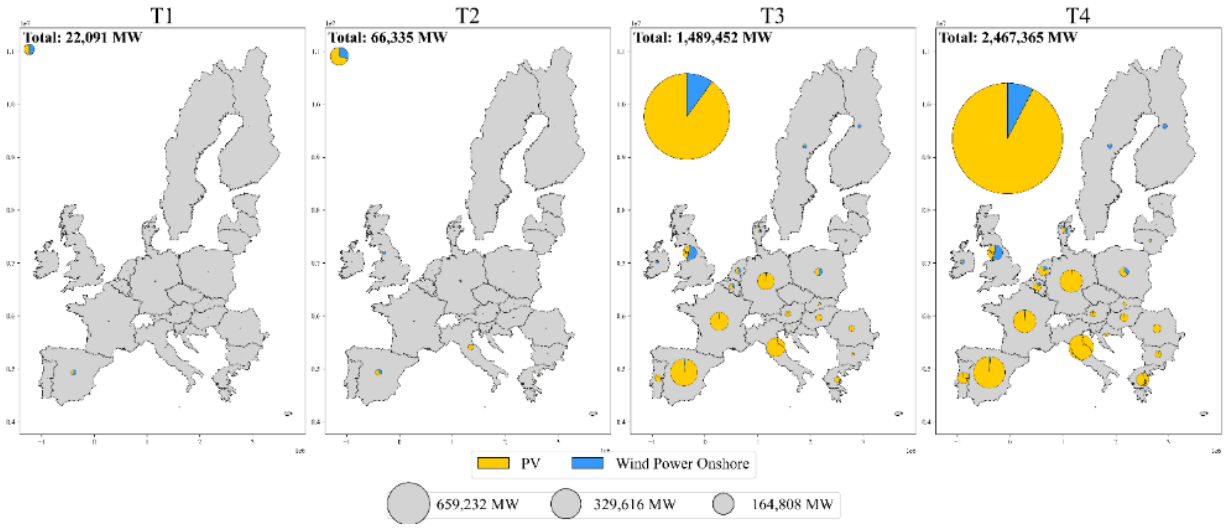


Figure 8-8: Expected RES installation in different countries over strategic time periods

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 multistage 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 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.

Figure 8-9 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%, 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 nar-

row 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.

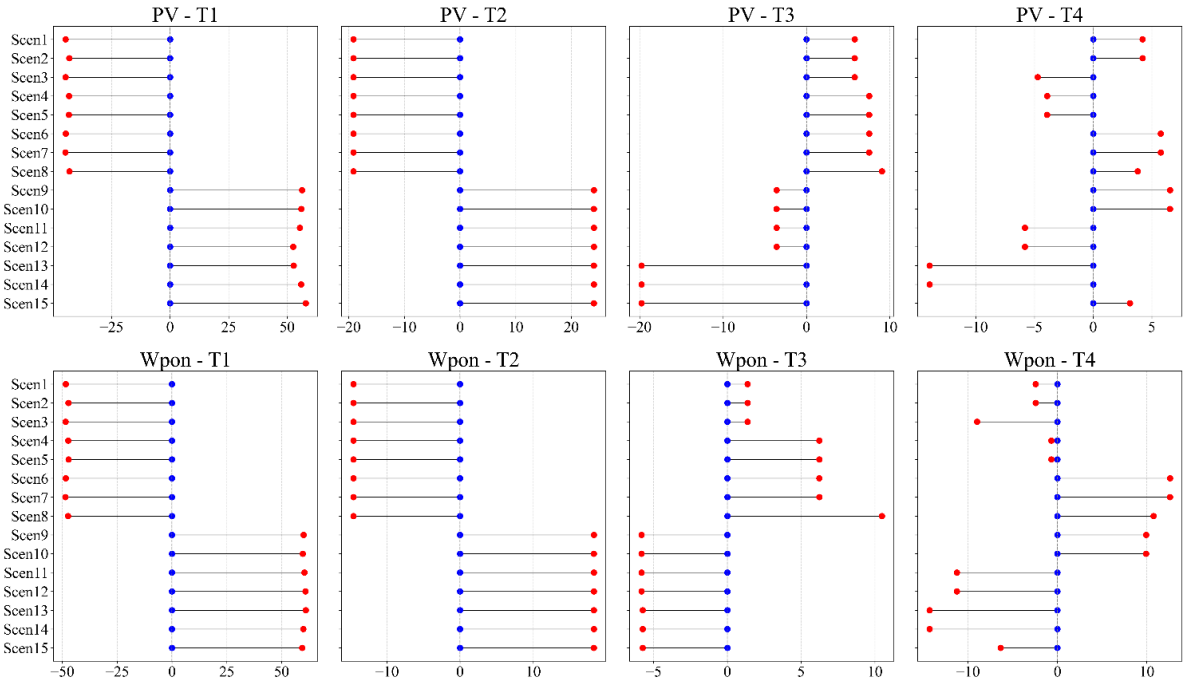


Figure 8-9: Percentage of deviation from expected RES installed in each scenario and time period

Figure 8-10 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 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 multi-channel 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.

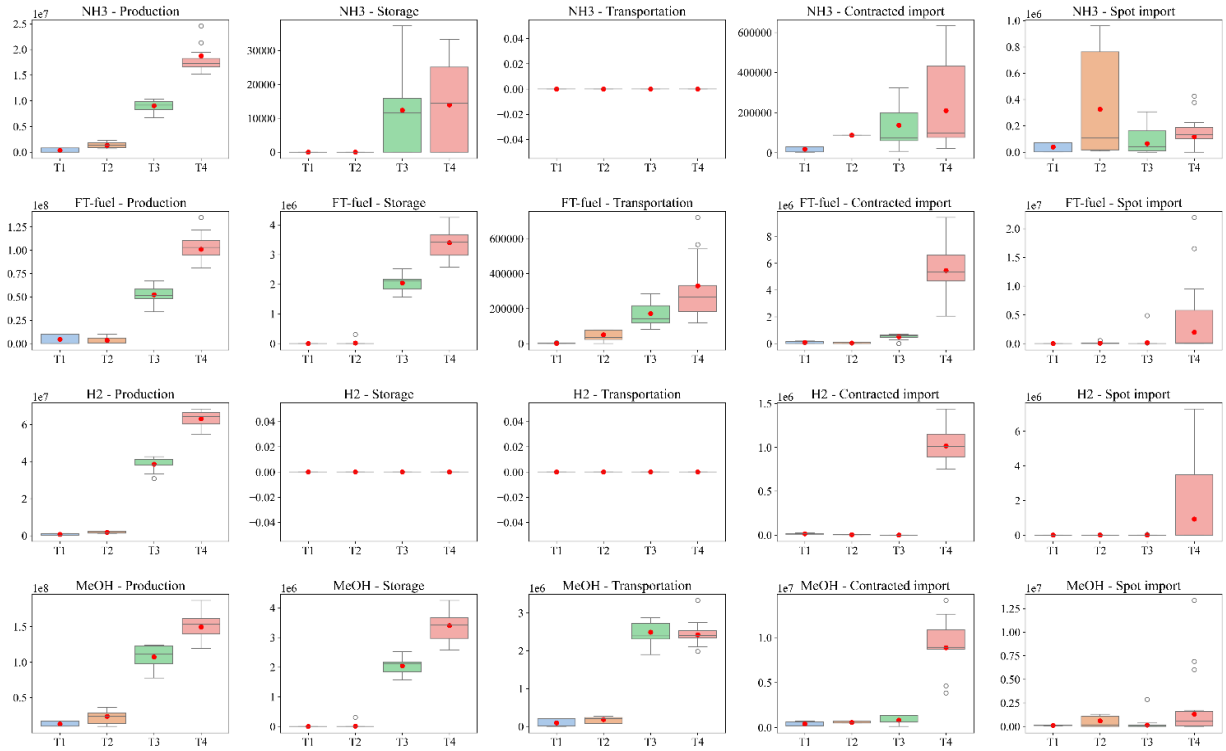


Figure 8-10: Demand fulfillment of different fuels across strategic time periods and for different scenarios

8.5.1 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.

Figure 8-11 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 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.

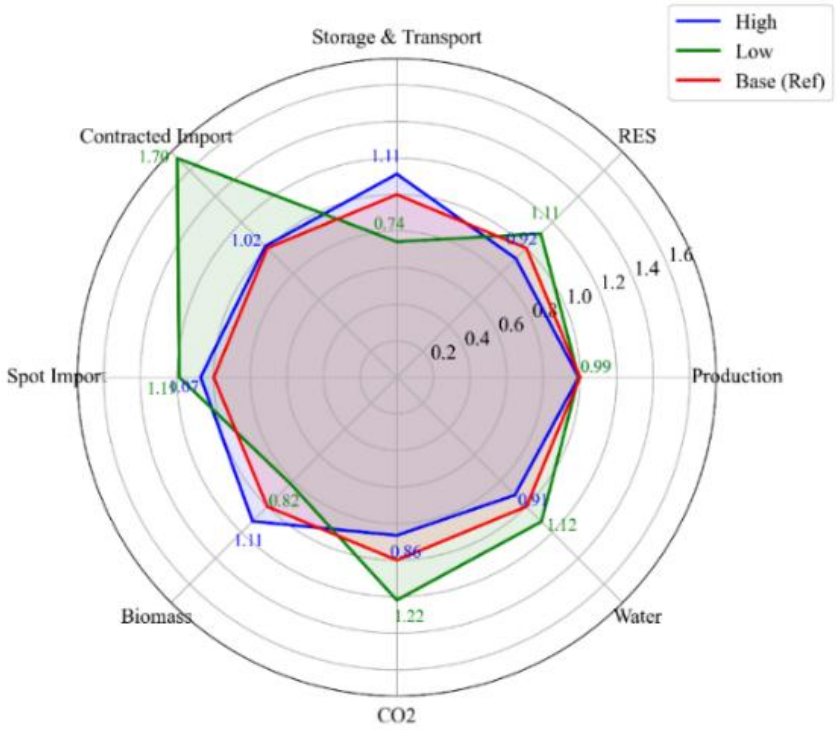


Figure 8-11: Changes in the cost items across different availability cases

8.5.2 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 & 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.

$$EVPI = MSSP - WS \quad \text{(for minimization problems)} \tag{8.30}$$

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.

$$RVMSS = EEV - MSSP/MSSP * 100 \quad \text{(for minimization problems)} \tag{8.31}$$

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 MSSPSP methods in scenarios characterized by high complexity and uncertainty. Table 8-3 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.

Table 8-3: Performance evaluation

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

8.6 Conclusion and outlook

This paper develops a multistage stochastic MILP framework to support long-term renewable-fuel logistics and supply chain 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 modelling 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 towards 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, the current MSSP framework has some limitations. Our study centers on demand uncertainty only. Other parameters, such as technology factors, costs, and availability of resources, are also subject to significant uncertainties but are not explicitly modeled. 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). Incorporating higher-frequency data could enhance realistic modelling but would further increase computational demands.

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 feedback. 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 renewable-fuel supply chains 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.

8.7 Supplementary materials

The full model input data, demand-scenario generation and reduction details, and complete results are provided in the supplementary materials available at https://doi.org/10.5281/zenodo.17633124

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8.9 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.

8.10 References

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