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Multi-objective optimization of renewable fuel supply chains regarding cost, land use, and water use

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HIGHLIGHTS

- A mathematical model for multi-objective optimization of renewable fuel supply chain with economic and environmental criteria
- A flexible, multi-period, and multi-stage supply chain design
- Considering multiple feedstocks, multiple products, and the seasonality of the resources
- Achieving a three-dimensional Pareto frontier and tradeoffs between pairs of objective functions
- European-wide case study is resolved using the proposed model

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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%.

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 [1]. 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 [2]. Since passenger and freight transport demand is expected to increase, defossilizing the transportation sector is essential to achieving emission reduction targets [3]. 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 [4]. Renewable hydrocarbon “drop-in” fuels, including methanol (MeOH), ethanol, dimethyl ethers (DME), oxymethylene ethers (OME_n), 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

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vehicles [5].

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 [6]. 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 [7]. H_2 production is expected to increase dramatically in the future [8]. 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 [9]. Besides, research studies identified MeOH and H_2 as promising potential carriers to store energy from fluctuating renewable electricity generation [10,11]. 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 [12]. Moreover, its combustion does not emit carbon dioxide, reducing greenhouse gas emissions and addressing environmental concerns [13,14]. 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 [15].

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 [16]. 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 [17].

Electricity from renewable power generation, carbon sources, and water are all needed to produce renewable hydrocarbon fuels [18]. 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% [19]. 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 [20].

The impact of (inter-)national policies and agreements on renewable energy is transforming the landscape [21]. 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%) [22]. 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 W_e/m^2 for wind, and $\sim$ 0.1 W_e/m^2 for biomass [23]. 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 [22].

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 [24]. 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 [25]. Humanity currently utilizes 26% of total terrestrial evapotranspiration and 54% of accessible runoff [26]. In agriculture, biomass production for food and fibre consumes about 86% of the freshwater used worldwide [27]. There is a close connection between the energy system and water usage. In particular, H_2 production depends heavily on water resources [28]. 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 [29]. 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. Section 4 discusses a case study of the renewable fuel supply chain for the European Union (EU) and the United Kingdom (UK). Section 5 presents the case study results and discussion. Finally, Section 6 and section 7 are the results and conclusion.

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. [30] 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 Pourhejazi and Kwon [31] 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 [32]. 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 ([33–36]). Only a few works address the modeling of multi-commodity and multi-product supply chains ([37,38]). 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 ([18,16,39]).

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 ([39,40]). 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 ([41–44]). 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 ([37,45–48]). Other works have considered environmental impacts as a second objective function as well ([49–51]).

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 [52] 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. [53] 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. [54] present a wind farm planning strategy prioritizing wildlife protection in Greece. Dhar et al. [55] 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 and Boettner [56] 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. [57] propose a mixed integer bi-objective optimization to achieve the highest reduction in the grey-water footprint of ethanol production at the lowest cost. Furthermore, many other works have considered greenhouse gas emissions as the environmental impact of renewable fuels ([49,58–60]).

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 ([47,49,61–63]). 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 ([39,58,64–66]). 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 ([67–71]). Garcia and You [72] note that Life Cycle Optimization (LCO) research often does not consider emissions from LUC and proposes a new LCO model that considers the global economy and environment by integrating LUC modeling. Sliz-Szkliniarz [73] 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. [74] 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 and Kim [75] 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. [76] 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-competing issues between bioenergy and non-energy systems at different land types. Tröndle [77] 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. [78] 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 need to be considered. Jin et al. [24] 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 ([79–83]). In this context, several works have investigated water usage in H_2 production processes ([84–88]). To the authors' best knowledge, there is a lack of work assessing water usage in renewable fuel supply chain optimization problems. Table 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

Table 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
[62]	Biomass			LUC Emissions			EU
[48]	Biomass	✓		Land Availability			US, EU
[49]	Biomass	✓	✓	LUC Emissions			Germany
[63]	Biomass			LUC Emissions			Malaysia
[67]	Solar	✓		LUC Emissions			EU, India, Japan, S-Korea
[72]	Biomass	✓	✓	LUC Emission			US, EU
[73]	Biomass, Wind, Solar			Land Availability			Poland
[74]	Biomass	✓		Land Allocation			Australia
[75]	Coal, Natural Gas, Nuclear, Hydroelectric, PV, Wind, Biomass			Land Transformation and Occupation			US
[58]	Biomass	✓	✓	Land Availability		✓	UK
[39]	CCUS, H_2-based Technologies	✓	✓	Land Availability		✓	UK
[64]	Biomass	✓		Land Availability			EU
[65]	Biomass	✓		Land Availability			World
[76]	Biomass	✓	✓	Land Availability			UK
[77]	Solar, Wind, Biomass	✓	✓	Land Required		✓	EU
[78]	Solar (Rooftop PV)			Land-used			China
[79]	Biomass				Water Footprint		EU
[80]	Biomass				Water Footprint		US
[81]	Biomass				Water Footprint		US
[83]	Biomass				Water Footprint		Niederland, Brazil, Zimbabwe
[84]	H_2				H_2 Water Consumption		EU
[87]	H_2				H_2 Water Consumption		US
[88]	H_2				H_2 Water Consumption		
This Work	Solar, Wind, Biomass	✓	✓	Land use Land Availability	Water Footprint H_2 Water Consumption	✓	EU+UK

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.

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 [89]. 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.

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. Fig. 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. [58] to represent and flexibly model our problem. Two different types of nodes exist in this approach. The first type (circles in Fig. 1) represents all the resources ($m \in M$) comprised of raw materials (biomass, CO_2 from point sources, electricity, water), intermediates (CO_2 from direct air capture, H_2) and final products (FT-fuels, MeOH, H_2). The second type of nodes (rectangles in Fig. 1) illustrates technologies that transform these resources. Additionally, we consider origins of resources ($o \in O$) in our model structure which consist of biomass of different types ($b \in B$) and sources of renewable electricity ($r \in RE$) are. For time periods we use the time aggregation approach based on Samsatli et al. [58], 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 needs 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. [37].

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 [90], 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) [91]. To calculate water needs for consumer products, a measure called "water footprint" was introduced by Hoekstra and Hung [92], and Hoekstra and Chapagain [27] 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

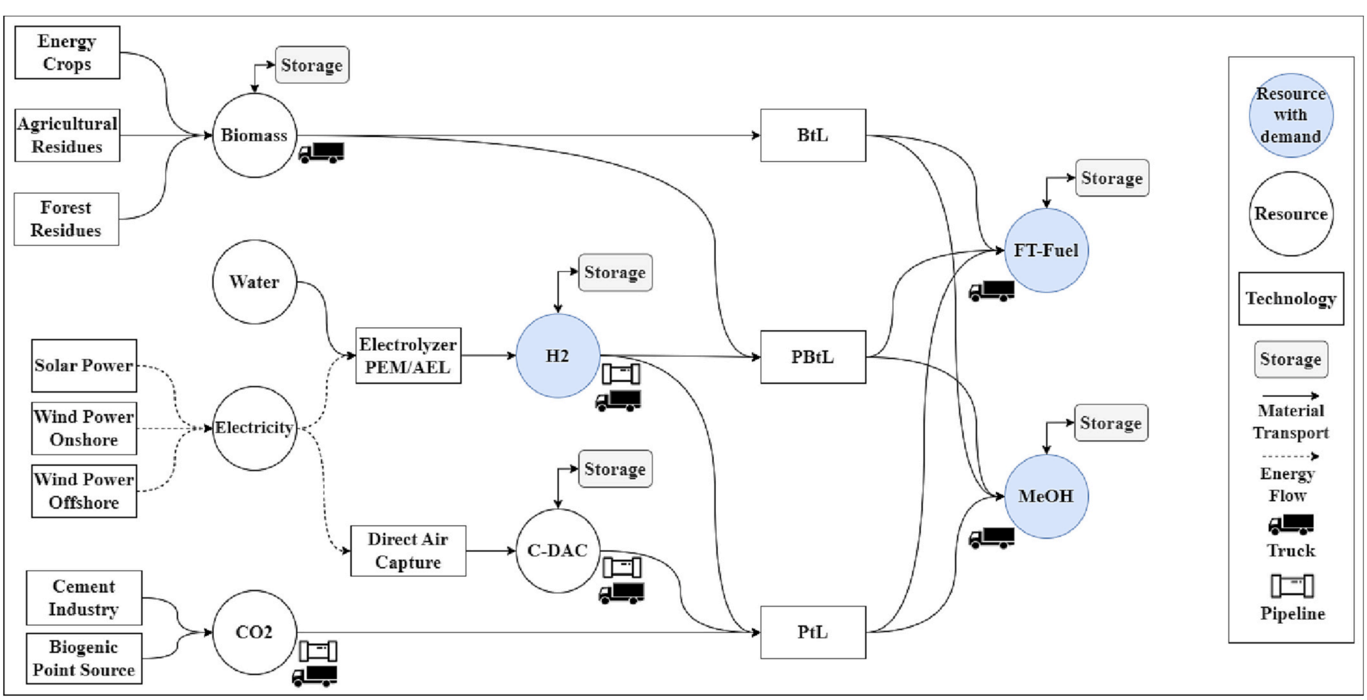

Fig. 1. Renewable fuel supply chain network.

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 [42,93]. 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 H_2 and CO_2 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.

3.2. Mathematical formulation

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

3.2.1. Nomenclature

I	Set of regions	$i,\acute{i} \in I$
$CI \subset I$	Set of locations of caverns	
M	Set of resources	$m \in M$
O	Set of resource origin	$o \in O$
$B \subset O$	Set of types of biomass	$b \in B$
$RE \subset O$	Set of renewable electricity sources	$r \in RE$
T_0	Set of planning periods with the start period	$T_0 \sim \{0\} \cup T$
$T \subset T_0$	Set of planning periods	$t \in T$
S	Set of seasons, S is a cyclic order	$s \in S$
P	Set of production technologies with different capacities	$p \in P$
L	Set of storage technologies	$l \in L$
Q	Set of transportation technologies	$q \in Q$
$Q_{inv} \subset Q$	Set of transportation technologies with different capacities that require an investment	
Resource/ Demand parameters		
R_{oits}	Potential of resource origin o at region i in period t in season s $[tonnes/season]$, $[MWh/season]$	
ϑ_{isr}	Capacity factor for renewable electricity source r in region i and season s [1]	
Θ_{ir}	Maximum installable capacity for renewable electricity source r in region i $[MW]$	
D_{mits}	Demand for resource m in region i in period t in season s $[tonnes/season]$	
μ_o	Share of resource origin o available for transportation fuel production	
η_m	Deterioration rate of resource m in storage $[tonnes/season]$	
υ	Maximum share of import for each resource in each decade to each region	
Production/ Storage/ Transportation parameters		
α_{mp}	Conversion rate (consumption, production) of resource m by production technology p $[tonnes/tonnes]$, $[MWh/tonnes]$	
AY_p	Strategic time period in which production technology p is available	
β_{om}	1, if resource m can be obtained from origin o; 0 otherwise	
K_p^{prod}	Capacity of production technology p $[tonnes/hour]$	
K_l^{stor}	Capacity of storage technology l per season $[tonnes/season]$	
K_q^{tran}	Capacity of transportation technology q $[tonnes/hour]$	
A_{lm}	Resource m that can be stored by storage technology l	
B_{qm}	Resources m that can be transported by transport technology q	
$d_{i\acute{i}}$	Distance between region i, $\acute{i}$ $[km]$	
$B_{i\acute{i}}^{truck}$	Regions $(i,\acute{i})$ that transportation is possible via trucks	
$B_{i\acute{i}}^{pipe}$	Regions $(i,\acute{i})$ that transportation is possible via pipelines	
Land/ Water related parameters		
L_{itb}	Available land for biomass type b in region i in period t $[km^2]$	
L_{itr}	Available land for renewable electricity source r in region i in period t $[km^2]$	
λ_b	Average crop yield of biomass type b $[tonnes/km^2]$	

(continued on next column)

(continued)

ρ_{ir}	Surface power density of renewable electricity source r in country i $[MW/km^2]$
χ	Water footprint of biomass from energy crops $[tonnes(water)/tonnes(biomass)]$
Cost related parameters	
τ	Discount rate [1]
ζ_t^{sp}	Discounting factor of each strategic period t [1]
ζ_t^{yp}	Discounting factor of each annual period t [1]
f_p^{prod}	Investment cost for production technology p $[€/plant]$
f_l^{stor}	Investment cost for storage technology l $[€/storage\ unit]$
f_q^{trans}	Distance-related investment costs for transportation technology q $[€/km/transportation\ infrastructure]$
c_p^{pod}	Annual O&M cost of production technology p $[€/year/plant]$
c_l^{stor}	Annual O&M costs of storage technology l $[€/year/storage\ unit]$
c_q^{trans}	Distance-related annual O&M costs of transportion technology q $[€/km/year/transportation\ infrastructure]$
$\nu_q^{trans,dis}$	Distance-related unit transport costs of transportation technology q $[€/tonnes/km]$
ν_q^{tran}	Unit transport costs of transportation technology q $[€/tonnes]$
v_{oit}	Unit purchasing costs of resource from origin o in region i in period t, $[€/tonnes]$ or $[€/MWh]$
ν_{mt}^{import}	Cost of importing product m in period t $[€/tonnes]$
Others	
n	Number of years per strategic time period
H	Number of hours per season
$\acute{H}$	Number of operating hours per season
Resource variables	
ω_{oist}	Utilization of resource origin o in region i during period t and season s $[tonnes/season]$, $[MWh/season]$
θ_{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 $[tonnes/season]$
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 $[tonnes/season]$
γ_{lit}	Number of storage units of storage technology l installed at region i up to period t
$z_{qmi\acute{i}ts}$	Amount of resource m transported from region i to $\acute{i}$ using transportation technology q in period t during season s $[tonnes/season]$
$\kappa_{qi\acute{i}t}$	Number of transportation infrastructures $q \in Q_{inv}$ installed between region i and $\acute{i}$ up to period t
ψ_{mit}^{import}	Amount of material m imported to region i in period t during each season $[tonnes/season]$
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

3.2.2. Objective functions

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

3.2.2.1. 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) cost of providing resources and 5) 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.

$$MinTC = \sum_{t \in T} \left(I_t^{inv,prod} + I_t^{inv,stor} + I_t^{inv,trans} + I_t^{op,prod} + I_t^{op,stor} + I_t^{op,trans} + I_t^{var,trans} + I_t^{var,res} + I_t^{import} \right) \tag{1}$$

3.2.2.2. 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 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, land use of energy crops changes over time if their utilization changes.

$$MinTL \tag{2}$$

$$TL = Max \left\{ \sum_i \left(\frac{\sum_s \omega_{bist}}{\lambda_b} + \sum_r \frac{\theta_{itr}}{\rho_{ir}} \right) \right\}, b \in \{energy\ crops\}, t \in T \tag{3}$$

3.2.2.3. 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.

$$Min\ TW = \sum_{t \in T} \sum_{i \in I} \sum_{s \in S} \left(\omega_{water,ist} + \chi \omega_{bist} \right), b \in \{energy\ crops\} \tag{4}$$

3.2.3. Constraints

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

3.2.3.1. Balance constraint. Constraints (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 ($z_{qmi\acute{i}ts} - z_{qm\acute{i}its}$) 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).

$$\sum_{O \in O} \omega_{oits}\, \beta_{om} + \sum_{p \in P | t \geq AY_p} \alpha_{mp}\, x_{pits} + \sum_{l \in L | (l,m) \in A_{lm}} \left((1-\eta_m) y_{lmit(s-1)} - y_{lmits} \right) + \sum_{\acute{i} \in I} \sum_{q \in Q | (q,m) \in B_{qm}} \left(z_{qm\acute{i}its} - z_{qmi\acute{i}ts} \right) + \psi_{mit}^{import} \geq D_{mits}, m \in M, i \in I, t \in T, s \in S \tag{5}$$

3.2.3.2. Production/storage/transportation capacity limitation. Constraints (6) limit the production rate of production technology p to its installed capacity. Constraints (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 (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 (9) ensure that only the correct form of transportation can transport resources.

$$x_{pits} \leq H\acute{K}_p^{prod} \delta_{pit}, \qquad p \in P, i \in I, t \in T, s \in S \tag{6}$$

$$y_{lmits} \leq K_l^{stor} \gamma_{lit}, \qquad t \in T, s \in S, (l,m) \in A_{lm}, \quad (l = caverns \rightarrow i \in CI) \bigwedge (l \neq caverns \rightarrow i \in I) \tag{7}$$

$$z_{qmi\acute{i}ts} \leq H\acute{K}_q^{trans} \kappa_{qi\acute{i}t}, \qquad q \in Q_{inv}, m \in M, i, \acute{i} \in I, t \in T, s \in S \tag{8}$$

$$z_{qmi\acute{i}ts} = 0, \qquad q \in Q, m \in M, i, \acute{i} \in I, t \in T, s \in S, \quad | B_{qm} = 0 \wedge i = \acute{i} \wedge B_{i\acute{i}}^{pipe} = 0 \wedge B_{i\acute{i}}^{truck} = 0 \tag{9}$$

3.2.3.3. Limitation of resource utilization/ import. Constraints (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 (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 (12) limit the installed capacity for solar, wind onshore, and wind offshore power to its maximum installable capacity in each region. According to constraint (13), only a portion of demand can be met by importing from outside the system boundary.

$$\omega_{oits} \leq \mu_o R_{oist}, \qquad o \in O \backslash RE, water, i \in I, t \in T, s \in S \tag{10}$$

$$\omega_{oits} \leq H \theta_{itr} \vartheta_{isr}, \qquad o \in RE, i \in I, t \in T, s \in S \tag{11}$$

$$\theta_{itr} \leq \Theta_{ir}, \qquad r \in RE, i \in I, t \in T \tag{12}$$

$$\psi_{mit}^{import} \leq \upsilon D_{mits}, \qquad m \in M, i \in I, t \in T, s \in S \tag{13}$$

3.2.3.4. Investment extensions constraints. Constraints (14–16) demonstrate that the number of installed production, storage, and transportation facilities is not allowed to decrease over time. Accordingly, constraints (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.

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

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

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

$$\theta_{i(t-1)r} \leq \theta_{itr}, \qquad r \in RE, i \in I, t \in T_0 \tag{17}$$

3.2.3.5. Land and water constraints. Constraints (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 cultivation of energy crops. Constraints (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 (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.

$$\frac{\sum_s \omega_{bist}}{\lambda_b} \leq L_{itb}, \qquad b \in \{energy\ crops\}, i \in I, t \in T \tag{18}$$

$$\frac{\theta_{itr}}{\rho_{ir}} \leq L_{itr}, \qquad r \in RE, i \in I, t \in T \tag{19}$$

$$\omega_{water,its} + \chi\omega_{energycrops,ist} \leq \mu_{water}\mathrm{R}_{water,ist}, \qquad i \in I, t \in T, s \in S \tag{20}$$

3.2.3.6. Cost calculations. Constraints (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 (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 (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 (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 (29) account for variable transportation costs with payload-related and distance-related components. Constraints (30) denote the cost of resource utilization. Constraints (31) illustrate the cost of importing from outside the system boundary.

$$\zeta_t^{sp} = (1+\tau)^{-n(t-1)}, \qquad t \in T \tag{21}$$

$$\zeta_t^{yp} = \left(\sum\nolimits_{i=1}^{n} (1+\tau)^{1-i}\right)\zeta_t^{sp}, \qquad t \in T \tag{22}$$

$$I_t^{inv,prod} = \zeta_t^{sp}\sum_{i\in I}\sum_{p\in P} f_p^{prod}\left(\delta_{pit} - \delta_{pi(t-1)}\right), \qquad t \in T \tag{23}$$

$$I_t^{inv,stor} = \zeta_t^{sp}\sum_{i\in I}\sum_{l\in L} f_l^{stor}\left(\gamma_{lit} - \gamma_{li(t-1)}\right), \qquad t \in T \tag{24}$$

$$I_t^{inv,trans} = \zeta_t^{sp}\sum_{i\in I}\sum_{i'\in I|i'\neq i}\sum_{q\in Q_{inv}} f_q^{trans} d_{ii'}\left(\kappa_{qii't} - \kappa_{qii'(t-1)}\right), \qquad t \in T \tag{25}$$

$$I_t^{op,prod} = \zeta_t^{yp}\sum_{i\in I}\sum_{p\in P} c_p^{prod}\delta_{pit}, \qquad t \in T \tag{26}$$

$$I_t^{op,stor} = \zeta_t^{yp}\sum_{i\in I}\sum_{l\in L} c_l^{stor}\gamma_{lit}, \qquad t \in T \tag{27}$$

$$I_t^{op,trans} = \zeta_t^{yp}\sum_{i\in I}\sum_{i'\in I|i'\neq i}\sum_{q\in Q} c_q^{trans} d_{ii'}\kappa_{qii't}, \qquad t \in T \tag{28}$$

$$I_t^{var,trans} = \zeta_t^{yp}\sum_{s\in S}\sum_{i\in I}\sum_{i'\in I|i'\neq i}\sum_{q\in Q}\sum_{m\in M}\left(\nu_q^{trans,dis} d_{ii'} + \nu_q^{tran}\right) z_{qmii'ts}, \qquad t \in T, \tag{29}$$

$$I_t^{var,res} = \zeta_t^{yp}\sum_{o\in O}\sum_{i\in I}\sum_{s\in S}(\omega_{oist}v_{oit}), \qquad t \in T \tag{30}$$

$$I_t^{import} = \zeta_t^{yp}\sum_{m\in M}\sum_{i\in I}\left(\nu_{mt}^{import}\psi_{mit}^{import}\right), \qquad t \in T \tag{31}$$

3.2.3.7. Variable types. Constraints (32–34) denote the type of variables.

$$\theta_{itr} \geq 0, \qquad i \in I, t \in T_0, r \in RE \tag{32}$$

$$z_{qmii'ts}, x_{pist}, y_{lmits}, \omega_{oist}, \psi_{mit}^{import} \geq 0, \tag{33}$$

$$q \in Q, p \in P, l \in L, m \in M, o \in O, i, i' \in I, t \in T, s \in S, |i \neq i'$$

$$\kappa_{qii't}, \delta_{pit}, \gamma_{lit} \in \mathbb{N}_0, \qquad q \in Q_{inv}, p \in P, l \in L, i, i' \in I, t \in T_0, | i \neq i' \tag{34}$$

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 (RHS) 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 [94]. This issue has been addressed by the application of the augmented ε–constraint method that was first developed by Mavrotas [95]. 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. Eq. (35) depict the improved augmented ε–constraint method where e_i are the RHS 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 ([96–98]), as well as supply chain optimization problems specifically [99]. This paper uses this improved augmented ε–constraint method to solve the multi-objective MILP problem and obtain the Pareto frontier.

$$Min\left(f_1(x) - eps\left(s_2/_{r_2} + \ldots + s_n/_{r_n}\right)\right)$$

$$st: f_2(x) + s_2 = e_2, \ldots$$

$$f_n(x) + s_n = e_n,$$

$$x \in S, s_i \in \mathbb{R}^+ \tag{35}$$

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 [100]. 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 [95,101]. 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 [100]. To mitigate biases, we employ careful problem formulation, thorough trade-off evaluation, and a lexicographic method for calculating RHS values.

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.

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: 2030–2040, T3: 2040–2050, T4: 2050–2060). 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 h [102]. 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 [103]. The same holds for land use as well. We use a discount rate of 3.5% per year based on Quarton, Samsatli [1] 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 [104]. 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 [105]. 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 [33]. We assume that available forest residues and agricultural residues are limited to 28% and 40% of their potential based on Cintas et al. [93] and Haase et al. [106], 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 H_2 production and the cultivation of energy crops, and freshwater potential in each country is based on the Eurostat database [107]. Fig. A1 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 H_2. Their techno-economic and cost data are based on the FVV study [108] and Vos et al. [109]. 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 A1 in the appendix shows the techno-economic data for all production pathways. Resource inputs for these production technologies are taken from Liebich et al. [17] and are shown in Table A2 in the appendix.

We consider two different capacities for CO_2 pipelines with related costs based on Fassihi et al. [110] and McCollum et al. [111]. Three different capacities with related costs are considered for the transportation of H_2 based on the planned European Hydrogen Backbone (EHB) initiative [112]. Although current natural gas pipelines can be repurposed to be used for H_2 transportation, we are only considering new pipelines based on EHB data [112]. 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 A3 in the appendix.

Biomass, CO_2 from DAC, H_2, FT-fuels, and MeOH can be stored in this network. Caverns are considered for storing H_2 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 are available in Table A4 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. Fig. A2 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 A5 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 and Behrens [113] to calculate an average crop yield. For this

Table 2
Data description.

Description	Symbol	Unit	Source
Demand	D_{mits}	[tonnes/season]	➢ FT-fuels: Siegemund et al. [104] ➢ H_2: EHB [112] ➢ MeOH: Irena [114], Alvardo [115]
The potential of resource origin	R_{oits}	[tonnes/season]	➢ Biomass: ENSPRESO - BIOMASS [119] ➢ CO_2: Siegemund et al. [104] ➢ Water: Eurostat [107]
Maximum installable capacity for electricity generation	Θ_i^{solar} Θ_i^{windon} $\Theta_i^{windoff}$	[MW]	➢ Solar Power: ENSPRESO - SOLAR - PV and CSP [120] ➢ Wind Power: ENSPRESO - WIND - ONSHORE and OFFSHORE [121]
Capacity factor	ϑ_{is}^{solar} ϑ_{is}^{windon} $\vartheta_{is}^{windoff}$	–	➢ Solar Power: ENSPRESO - SOLAR - PV and CSP [120] ➢ Wind Power: ENSPRESO - WIND - ONSHORE and OFFSHORE [121]
The conversion factor of resource m by production technology *p*	α_{mp}	[tonnes/t], [MWh/t]	Liebich et al. [17]
Capacities	K_p^{prod} K_l^{stor} K_q^{tran}	[tonnes/h], [tonnes/season]	➢ Production technology: Liebich et al. [17], Analogues to FVV study for 2030–2050 [108] ➢ Storage technology: FVV [108], Reuß et al. [122], Akhtari et al. [123] ➢ Transport technology: Fasihi [110], McCollum [111], EHB [124]
The period that production technology ***p*** is available to be installed	AT_p	–	Based on the FVV for 2030–2050 [108]
Deterioration rate of resources	η_m	[tonnes/season]	➢ Biomass: Xie et al. [125], You and Wang [42]
Available land	L_{it}^{bio} L_{it}^{solar} L_{it}^{wind}	[km^2]	➢ Biomass: ENSPRESO - BIOMASS [119] ➢ Solar Power: ENSPRESO - SOLAR - PV and CSP [120] ➢ Wind Power: ENSPRESO - WIND - ONSHORE and OFFSHORE [121]
The lower heating value	LHV_b	[MJ/kg]	ENSPRESO - BIOMASS [119]
Power densities	$\rho_b^{bio}, \rho^{solar}$ ρ^{windon} $\rho^{windoff}$	[MW/km^2]	➢ Biomass: van Zalk et al. [113] ➢ Solar Power: ENSPRESO - SOLAR - PV and CSP [120] ➢ Wind Power: ENSPRESO - WIND - ONSHORE and OFFSHORE [121]
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. [17], Analogues to FVV study for 2030–2050 [108] ➢ Storage technology: FVV study [108], Reuß et al. [122], Akhtari et al. [123] ➢ Transport technology: Fasihi [110], McCollum [111], EHB [124]
Distance-related unit transport costs	$\nu_q^{trans,dis}$	[€/tonnes/km]	Reuß et al. [122], Leduc [126], Danish Energy Agency [127]
Unit transport costs of transport technology	ν_q^{tran}	[€/tonnes]	Reuß et al. [122], Leduc [126], Fasihi [110], McCollum [111], Danish Energy Agency [127]
Unit purchasing costs of resource	ν_{oit}	[€/tonnes], [€/MWh]	➢ Biomass: ENSPRESO - BIOMASS [119] ➢ Water: The governance of water services in Europe [116], Varone and Ferrari [128] ➢ CO_2: Brynolf et al. [117] ➢ Solar: Searle and Christensen [118] ➢ Wind: Searle and Christensen [118] ➢ Import: FVV study [108]

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. [104]. H_2 demand is calculated based on an EHB study by summing up the demand for H_2 in aviation and heavy-duty road transport [8]. Since we could not find a suitable study on the future demand for MeOH in the transportation sector, we considered the IRENA projection [114] 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 [115]. 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 A6 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 limited available amount of import. Based on this work and using interpolation, the import cost is determined and shown in Table A7 in the appendix [108].

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 [116]. The price for supplying CO_2 from industry and biogenic sources is based on Brynolf et al. [117]. Finally, the price of electricity provided by solar and wind power without taxes and grid fees is based on Searle and Christensen [118]. All price data are available in Tables A8 and A9 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 5000 and 20,000 s, respectively. The runtime of each iteration may vary depending on the epsilon values (RHS) of the AUG-MECON method. The model is being solved using an Intel(R) Core(TM) i7-8700K processor @ 3.70GHz, with 3696 MHz, 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 2.

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 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.

Fig. 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.

Table 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.

Fig. 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 Fig. 3.

An illustration of the trade-off between pairs of objective functions is provided in Figs. 4 and 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% (Fig. 4). Similarly, with different values of land use, decreasing water use by 3.5%, the cost only increases by 13.3% (Fig. 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.

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 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

Table 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 tonnes)
Cost-optimal solution	5.89[a]	4595	631,329
Land-optimal solution	160.13	879	8,312,471
Water-optimal solution	121.47	4168	2313

[a] Underline: The optimal value of each single objective function

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

Strategic time period \Water amount [Million tonnes]	Cost-optimal solution		Water-optimal solution	
	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	1129	0	1175

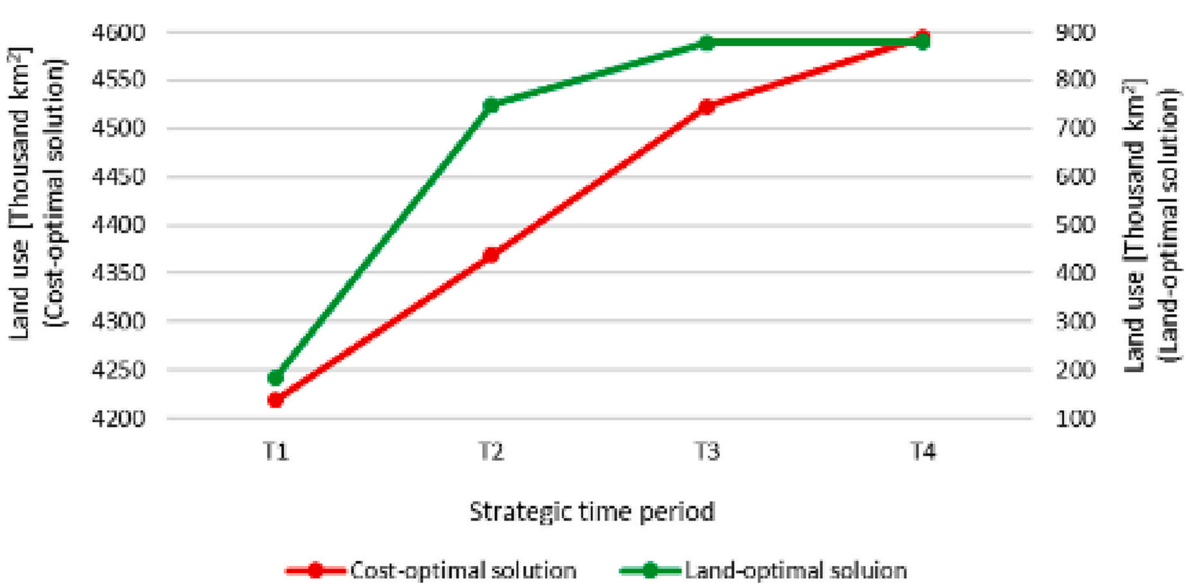

Fig. 2. Comparison of the development of total land use obtained by the cost-optimal and land-optimal solutions over the planning horizon.

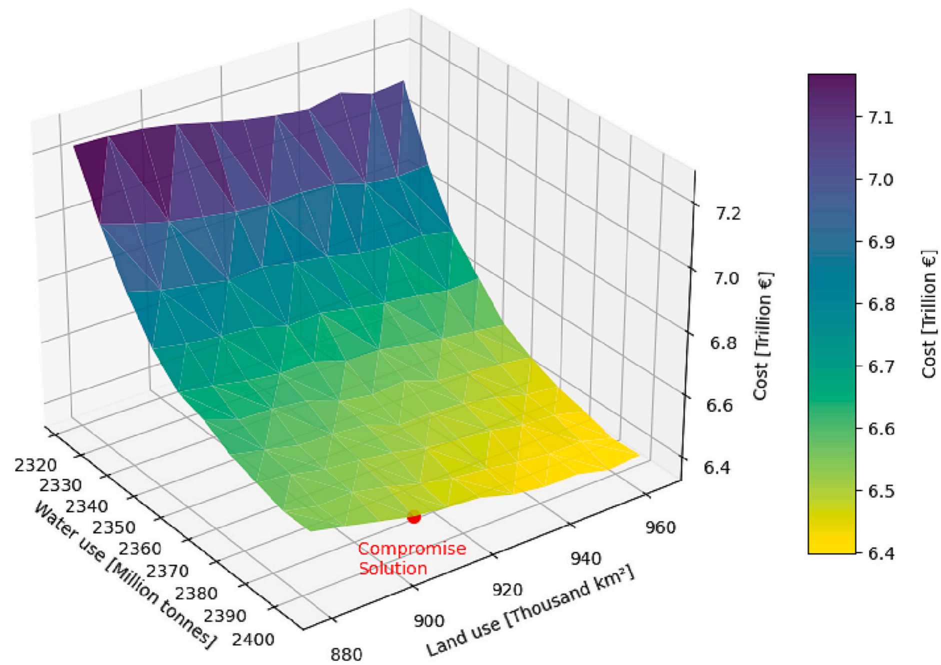

Fig. 3. Pareto-efficient layer.

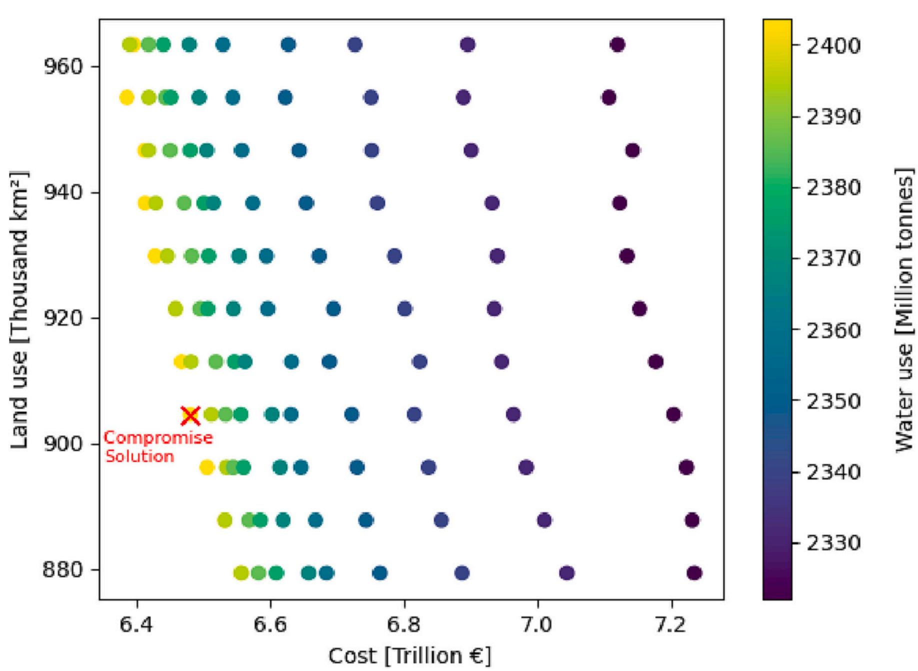

Fig. 4. Trade-offs between cost and land use. Water use is shown by the color and the color bar.

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 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%.

Fig. 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,

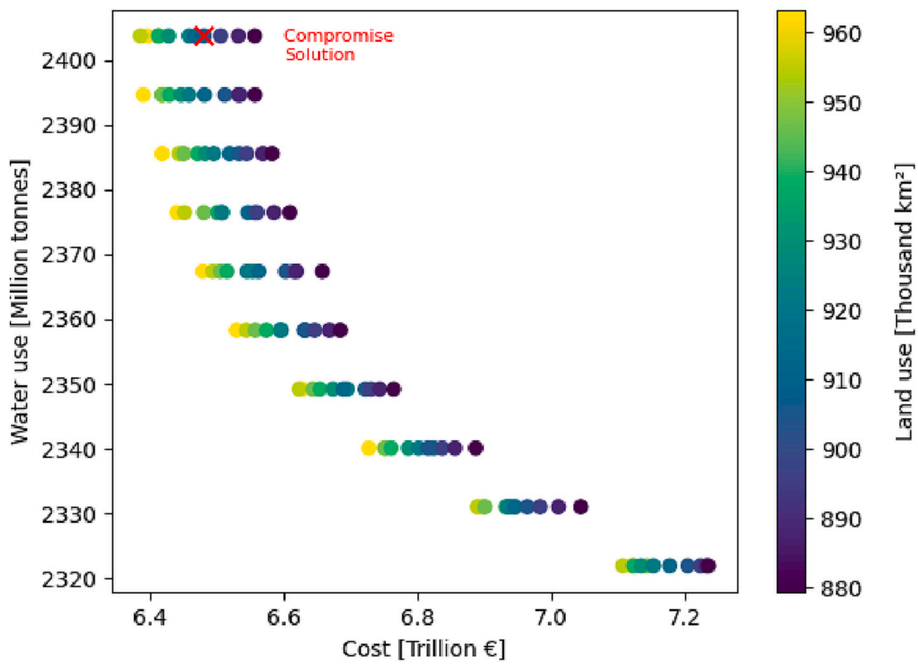

Fig. 5. Trade-offs between cost and water use. Land use is shown by the color and the color bar.

Table 5
Compromise solution selected from Pareto-frontier.

	Cost value (Trillion €)	Land use value (Thousand km^2)	Water use value (Million tonnes)
Solution from Pareto frontier	6.48	905	2404

Table 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	7403	0.13%	7463	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	1910	0.03%	1672	0.03%
Investment cost of transportation	4891	0.08%	5122	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	3152	0.05%	2310	0.04%
Unit transportation cost	10,870	0.18%	6617	0.10%
Water cost	23,105	0.39%	26,501	0.41%

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.

Table 7 shows the water used in the cost-optimal and compromise solution. The amount of H_2 produced in the cost-optimal and the compromise solution respectively is 243 and 265 [Million tonnes].

Figs. 7 and 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.

Fig. 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.

Fig. 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.

In total, 15.09 TW of renewable electricity is installed over all countries in the cost-optimal solution. In the compromise solution, 4.94

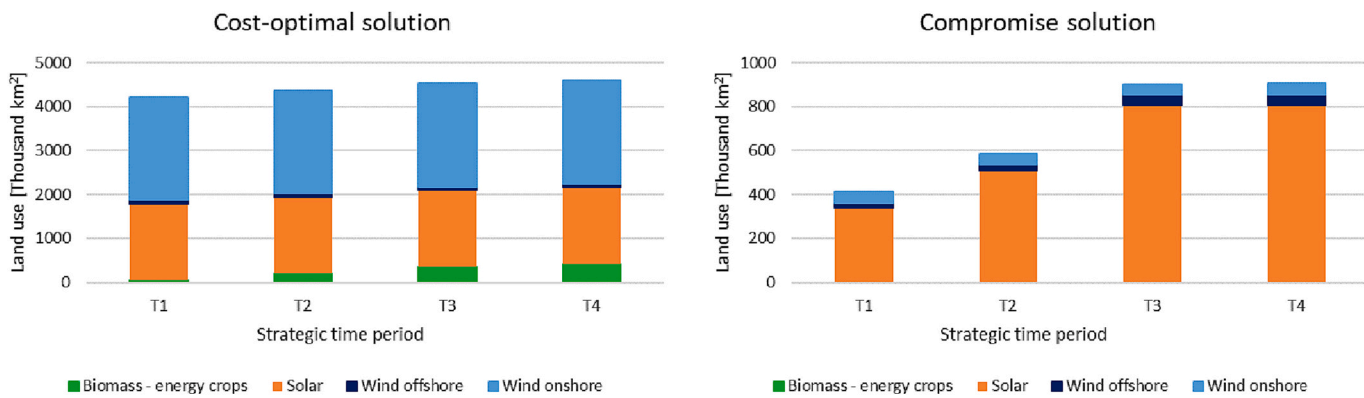

Fig. 6. Land use in the cost-optimal and compromise solutions.

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

Strategic time period \Water amount [Million tonnes]	Cost-optimal solution		Compromise solution	
	Energy crops	H2 production	Energy crops	H2 production
T1	31,176	90	0	86
T2	122,516	255	0	275
T3	215,985	813	0	850
T4	259,365	1129	0	1192

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 4580 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. 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 RHS 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. Furthermore, our results show the necessity for a lesser amount of import than permitted by our assumptions.

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 capacity 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

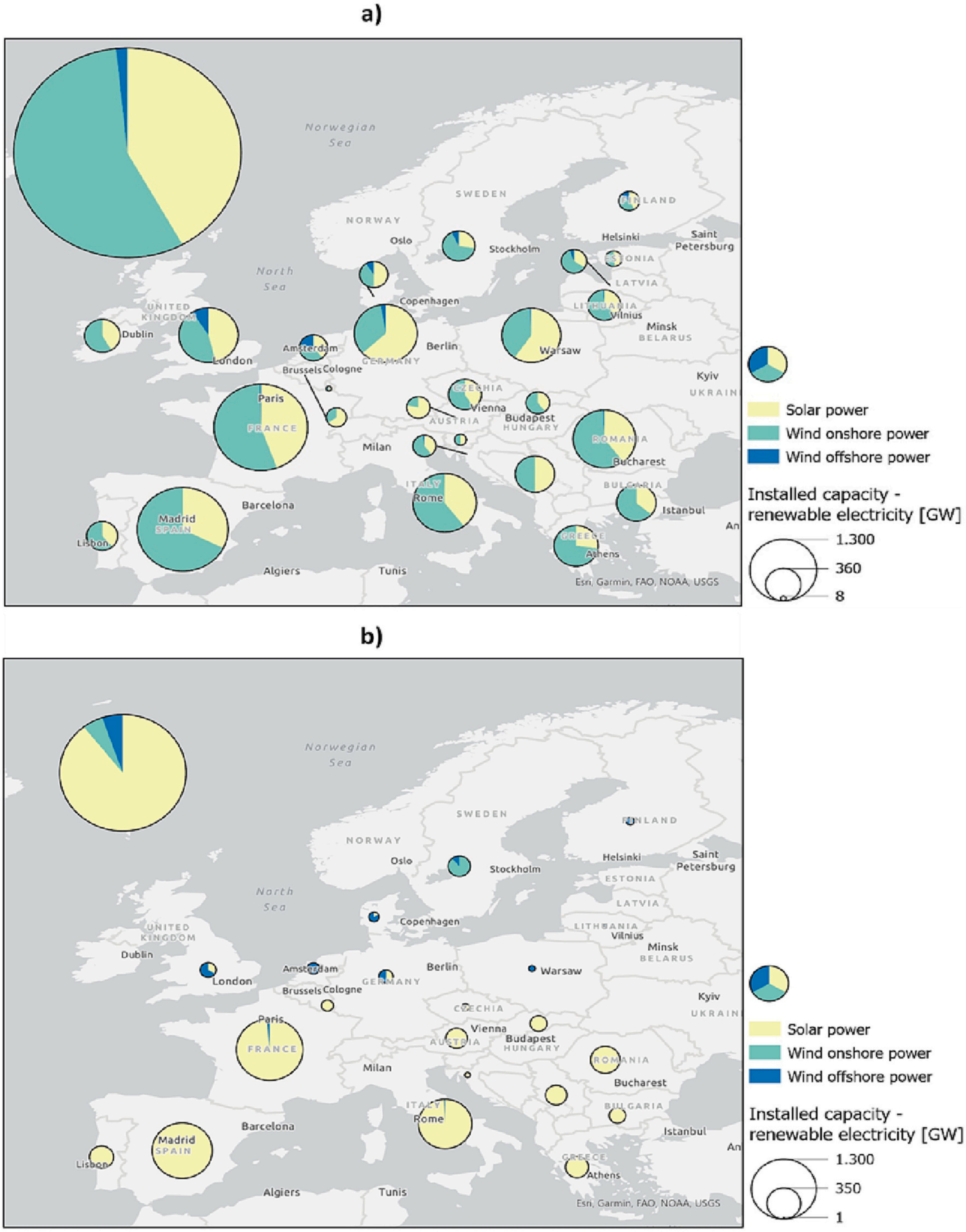

Fig. 7. Share of land used and installed capacity of renewable electricity a) In cost-optimal solution, b)In compromise solution.

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

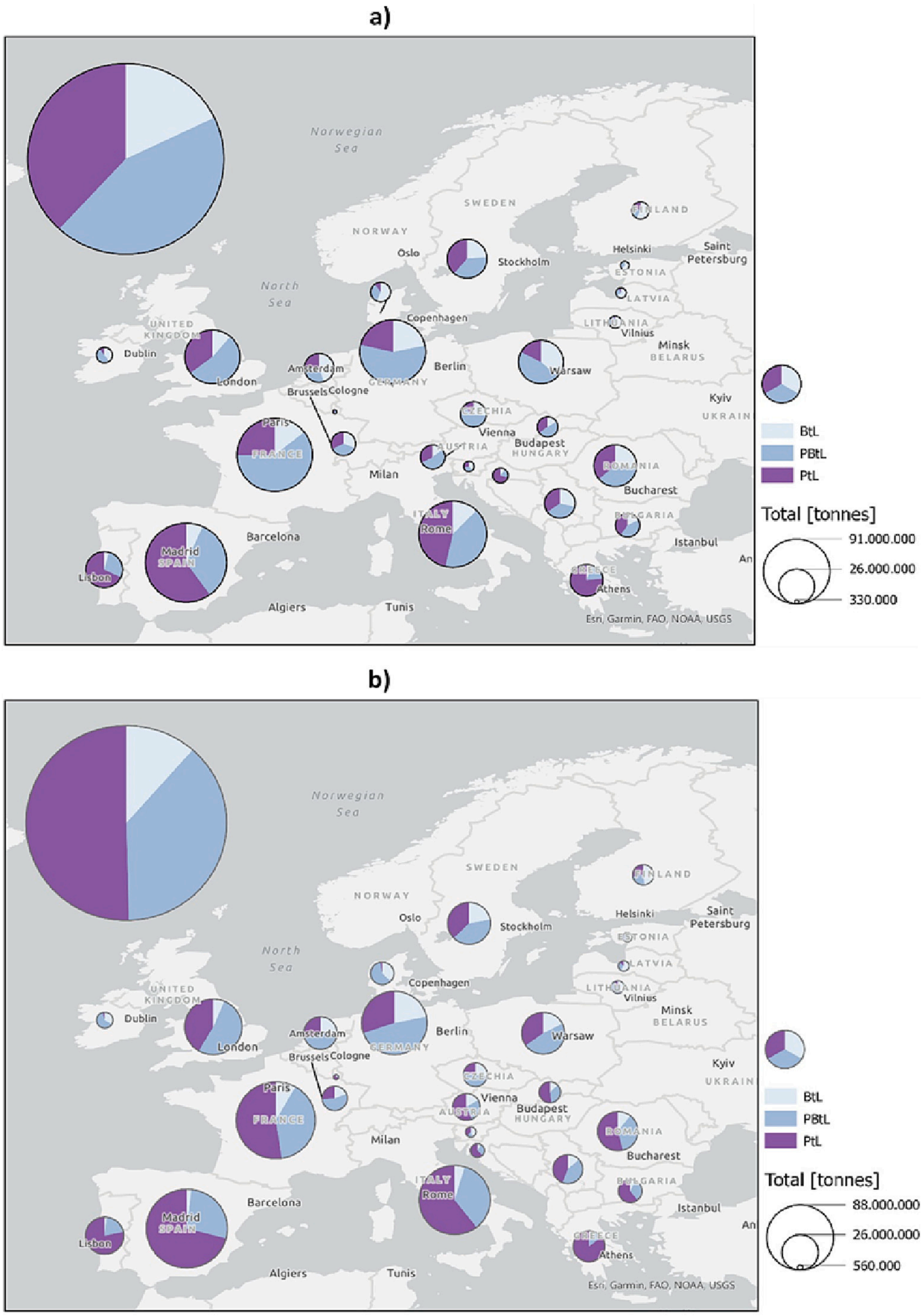

Fig. 8. Share of each production technology and amount of produced fuels a) In cost-optimal solution, b) In compromise solution.

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 strategically 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, for which in some cases we found 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 parameters also impact system costs. Additionally, parameters like power density and water usage play a role in meeting environmental criteria.

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. A mathematical model is proposed for designing a multi-period, long-term, multi-product, and multi-feedstock supply chain network of renewable fuels targeted at the transportation sector 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 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 objective functions. Considering Pareto-frontier solutions and trade-offs is crucial. In our study, we discover a solution that achieves a nearly optimal value of land and water use, with only a 10% increase in total cost. Depending on the prioritized criteria within the scope of their availability, the utilization of land and water can vary significantly. Results show that in none of the economic and environmental solutions, the pre-dominant production pathway is BtL indicating that renewable electricity and CO2 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. Based on current and projected installations of solar and wind power in the EU, achieving the required amount of wind power for our case study's compromise solution is realistic. However, meeting the required amount of solar power would require investment in additional 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. 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 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.

CRediT authorship contribution statement

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

Declaration of Competing Interest

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

Data availability

Data will be made available on request.

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Appendix A. Input data

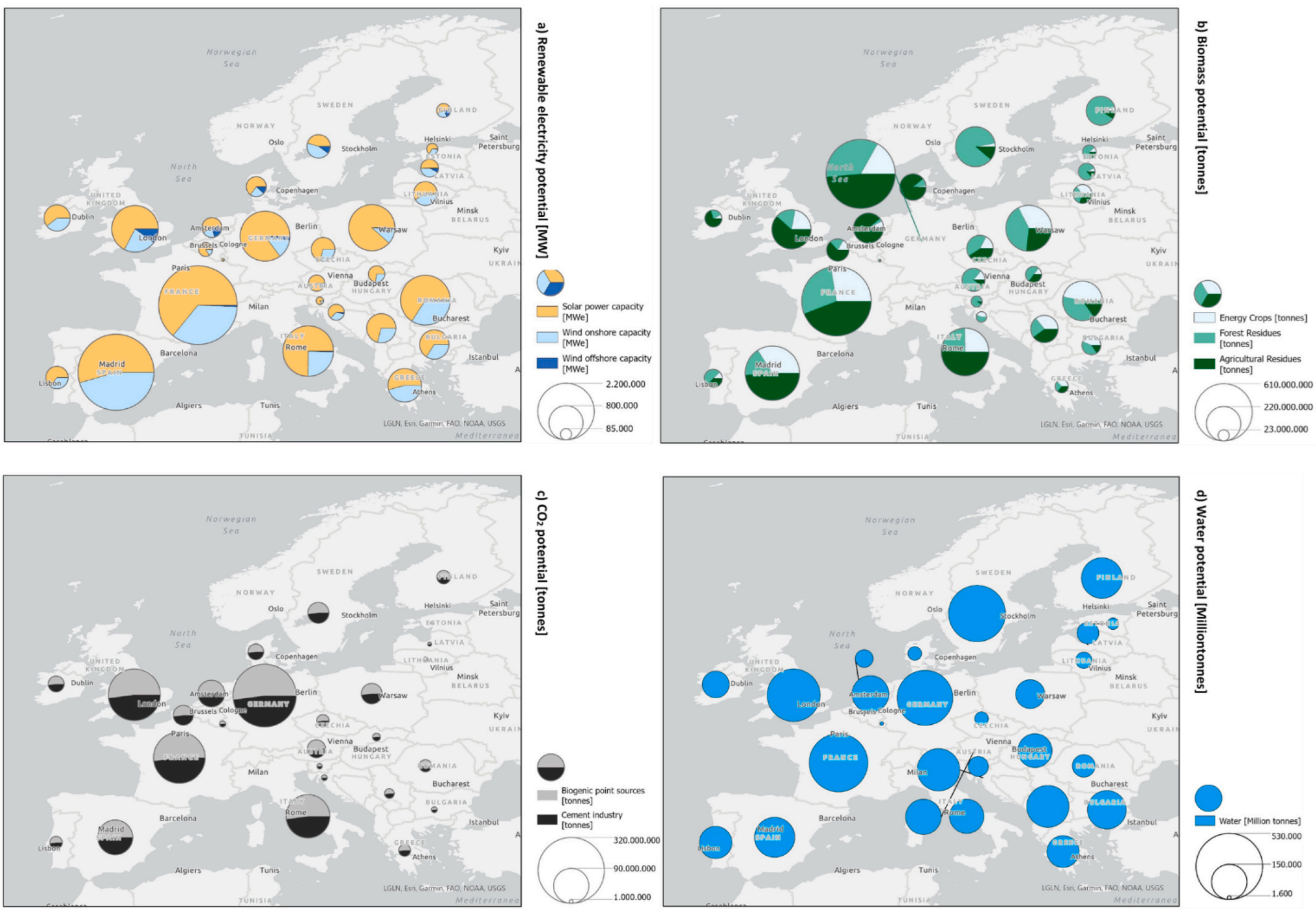

Fig. A1. Potential of resources in EU countries a)Renewable electricity potential b)Biomass potential c)CO_2 potential d)Water potential based on [100,104,119–121].

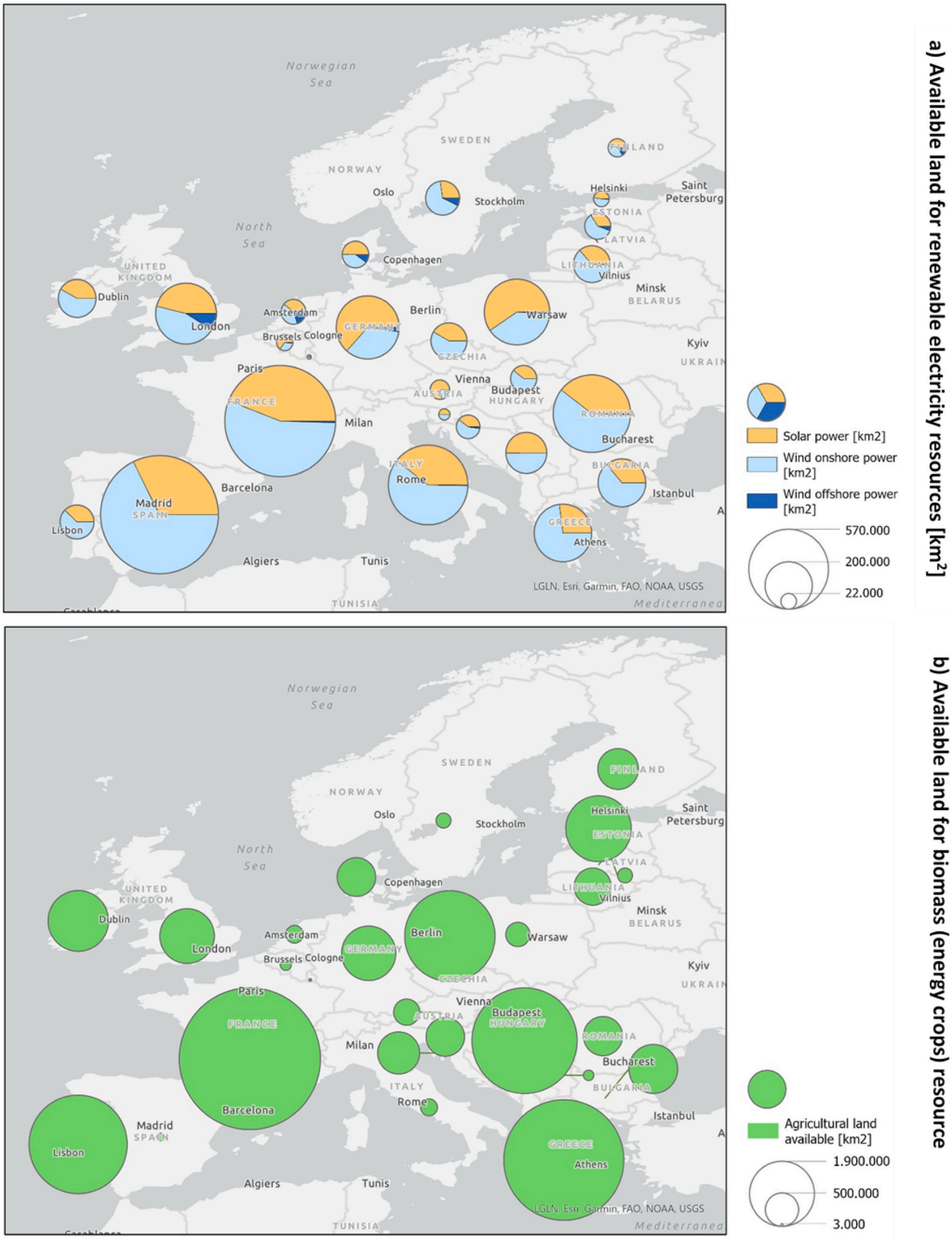

Fig. A2. Available land for different renewable resources in each EU country a)Renewable electricity b)Energy crops based on [119–121].

Table A1
Techno-economic data of production technologies based on [105,107,109,111].

Technology	Product	Capacity per plant [tonnes/h]	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 electrolysis	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 electrolysis	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 A2
Material and energy inputs of production technologies based on [107].

Resource inputs ([tonnes/tonnes], [MWh/tonnes])/ 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 A3
Transportation data based on [105,107,109,111].

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

Table A4
Storage data based on [105,109,111].

	Capacity [tonnes]	Investment cost [€]	O&M cost [€/year]
Fuel storage	77,000	70,789,000	2% of Investment cost
H_2 storage	3984	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 A5
Country-specific surface power density based on [18,112].

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 A6
Fuel demand based on [100,111,114,115].

Fuel demand [tonnes]\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 A7
Price of import based on [105].

Fuel price [€/tonne]\Period	1	2	3	4
FT-fuel	4495	3966	3438	2910
H_2	2367	2091	1816	1540
MeOH	6333	5666	5000	4333

Table A8
Price of CO_2 based on [117].

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

Table A9
Price of biomass, water and renewable electricity based on [116,118,119,124].

Country	Average price of energy crops [€/tonnes]	Average price of agricultural residues [€/tonnes]	Average price of forest residues [€/tonnes]	Average price of water[€/tonnes]	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

References

[1] Nations Unies. Convention - cadre sur les changements climatiques, Adoption de l'Accord de Paris. Cop 21 2015;21930:39.
[2] IEA. Transport. Paris: IEA; 2022. https://www.iea.org/reports/transport. License: CC BY 4.0 2022.
[3] European Environment Agency. Transport and environment report 2021: Decarbonising road transport – The role of vehicles, fuels and transport demand. 2022. p. 1–92. https://www.eea.europa.eu//publications/transport-and-environment-report-2021.
[4] Fasihi M, Bogdanov D, Breyer C. Long-term hydrocarbon trade options for the Maghreb region and Europe-renewable energy based synthetic fuels for a net zero emissions world. Sustain 2017:9. https://doi.org/10.3390/su9020306.
[5] Dry ME. High quality diesel via the Fischer-Tropsch process - a review. J Chem Technol Biotechnol 2002;77:43–50. https://doi.org/10.1002/jctb.527.
[6] Schemme S, Samsun RC, Peters R, Stolten D. Power-to-fuel as a key to sustainable transport systems – an analysis of diesel fuels produced from CO2 and renewable electricity. Fuel 2017;205:198–221. https://doi.org/10.1016/j.fuel.2017.05.061.
[7] Abdin Z, Zafaranloo A, Rafiee A, Mérida W, Lipiński W, Khalilpour KR. Hydrogen as an energy vector. Renew Sustain Energy Rev 2020:120. https://doi.org/10.1016/j.rser.2019.109620.
[8] Wang A, Jens J, Mavins D, Moultak M, Schimmel M, Van Der Leun K, et al. Analysing future demand, supply, and transport of hydrogen. Eur Hydrog Backbone 2021:70.
[9] Olah GA. Beyond oil and gas: the methanol economy. Angew Chem Int Ed 2005;44:2636–9. https://doi.org/10.1002/anie.200462121.
[10] Bos MJ, Kersten SRA, Brilman DWF. Wind power to methanol: renewable methanol production using electricity, electrolysis of water and CO2 air capture. Appl Energy 2020;264:114672. https://doi.org/10.1016/j.apenergy.2020.114672.
[11] Yan Z, Hitt JL, Turner JA, Mallouk TE. Renewable electricity storage using electrolysis. Proc Natl Acad Sci U S A 2020;117:12558–63. https://doi.org/10.1073/pnas.1821686116.
[12] DNV GL. Maritime. Assessment of selected Ternative fuels and technologies. Imo 2019;391:1–48.
[13] Sagel VN, Rouwenhorst KHR, Faria JA. Green ammonia enables sustainable energy production in small island developing states: a case study on the island of Curaçao. Renew Sustain Energy Rev 2022;161:112381.
[14] Xing H, Stuart C, Spence S, Chen H. Alternative fuel options for low carbon maritime transportation: pathways to 2050. J Clean Prod 2021;297:126651. https://doi.org/10.1016/j.jclepro.2021.126651.
[15] Jones Nicola From fertilizer to fuel: can 'green' Ammonia be a climate fix? [online]. 2022. Available: https://e360.yale.edu/features/from-fertilizer-to-fuel-can-green-ammonia-be-a-climate-fix.
[16] Albrecht FG, König DH, Baucks N, Dietrich RU. A standardized methodology for the techno-economic evaluation of alternative fuels – a case study. Fuel 2017;194:511–26. https://doi.org/10.1016/j.fuel.2016.12.003.
[17] Liebich Axel, Fröhlich Thomas, Münter Daniel, Fehrenbach Horst, Giegrich Jürgen, Köppen Susanne, et al. System comparison of storable energy carriers from renewable energies - final report. Umwelt Bundesamt 2021;3:77. https://doi.org/10.13140/RG.2.2.31054.38723.
[18] Albrecht FG, Van Nguyen T. Prospects of electrofuels to defossilize transportation in Denmark – a techno-economic and ecological analysis. Energy 2020;192:116511. https://doi.org/10.1016/j.energy.2019.116511.
[19] EEA. Share of energy consumption from renewable sources in Europe – European Environment Agency. https://www.eea.europa.eu/data-and-maps/indicators/renewable-gross-final-energy-consumption-5/assessment; 2021.
[20] Teske S, Pregger T, Simon S, Naegler T, Pagenkopf J, Deniz Ö, et al. It is still possible to achieve the Paris climate agreement: regional, sectoral, and land-use pathways. Energies 2021;14:2103. https://doi.org/10.3390/en14082103.
[21] Enserink M, Van Etteger R, Van den Brink A, Stremke S. To support or oppose renewable energy projects? A systematic literature review on the factors

influencing landscape design and social acceptance. Energy Res Soc Sci 2022;91: 102740. https://doi.org/10.1016/j.erss.2022.102740.
[22] Lovering J, Swain M, Blomqvist L, Hernandez RR. Land-use intensity of electricity production and tomorrow's energy landscape. PloS One 2022:17. https://doi.org/10.1371/journal.pone.0270155.
[23] Capellán-Pérez I, de Castro C, Arto I. Assessing vulnerabilities and limits in the transition to renewable energies: land requirements under 100% solar energy scenarios. Renew Sustain Energy Rev 2017;77:760–82. https://doi.org/10.1016/j.rser.2017.03.137.
[24] Jin Y, Behrens P, Tukker A, Scherer L. Water use of electricity technologies: a global meta-analysis. Renew Sustain Energy Rev 2019;115:109391. https://doi.org/10.1016/j.rser.2019.109391.
[25] Postel SL. Entering an era of water scarcity: the challenges ahead. Ecol Appl 2000; 10:941–8. https://doi.org/10.1890/1051-0761(2000)010[0941:EAEOWS]2.0.CO;2.
[26] Postel SL, Daily GC, Ehrlich PR. Human appropriation of renewable fresh water. Science (80-) 1996;271:785–8. https://doi.org/10.1126/science.271.5250.785.
[27] Hoekstra AY, Chapagain AK. Water footprints of nations: water use by people as a function of their consumption pattern. Water Resour Manag 2006;21:35–48. https://doi.org/10.1007/s11269-006-9039-x.
[28] Howells M, Hermann S, Welsch M, Bazilian M, Segerström R, Alfstad T, et al. Integrated analysis of climate change, land-use, energy and water strategies. Nat Clim Chang 2013;3:621–6. https://doi.org/10.1038/nclimate1789.
[29] Ramos EP, Sridharan V, Alfstad T, Niet T, Shivakumar A, Howells MI, et al. Climate, land, energy and water systems interactions – from key concepts to model implementation with OSeMOSYS. Environ Sci Policy 2022;136:696–716. https://doi.org/10.1016/j.envsci.2022.07.007.
[30] Matinrad N, Roghanian E, Rasi Z. Supply chain network optimization: a review of classification, models, solution techniques and future research. Uncertain Supply Chain Manag 2013;1:1–24. https://doi.org/10.5267/j.uscm.2013.05.003.
[31] Pourhejazy P, Kwon OK. The new generation of operations research methods in supply chain optimization: a review. Sustain 2016:8. https://doi.org/10.3390/su8101033.
[32] Melo MT, Nickel S, Saldanha-da-Gama F. Facility location and supply chain management - a review. Eur J Oper Res 2009;196:401–12. https://doi.org/10.1016/j.ejor.2008.05.007.
[33] Čuček L, Martín M, Grossmann IE, Kravanja Z. Multi-period synthesis of optimally integrated biomass and bioenergy supply network. Comput Chem Eng 2014;66: 57–70. https://doi.org/10.1016/j.compchemeng.2014.02.020.
[34] Malladi KT, Sowlati T. Biomass logistics: a review of important features, optimization modeling and the new trends. Renew Sustain Energy Rev 2018;94: 587–99. https://doi.org/10.1016/j.rser.2018.06.052.
[35] Zandi Atashbar N, Labadie N, Prins C. Modelling and optimisation of biomass supply chains: a review. Int J Prod Res 2018;56:3482–506. https://doi.org/10.1080/00207543.2017.1343506.
[36] Yue D, You F, Snyder SW. Biomass-to-bioenergy and biofuel supply chain optimization: overview, key issues and challenges. Comput Chem Eng 2014;66: 36–56. https://doi.org/10.1016/j.compchemeng.2013.11.016.
[37] Wolff M, Becker T, Walther G. Long-term design and analysis of renewable fuel supply chains – an integrated approach considering seasonal resource availability. Eur J Oper Res 2023;304:745–62. https://doi.org/10.1016/j.ejor.2022.04.001.
[38] Rentizelas AA, Tolis AJ, Tatsiopoulos IP. Logistics issues of biomass: the storage problem and the multi-biomass supply chain. Renew Sustain Energy Rev 2009;13: 887–94. https://doi.org/10.1016/j.rser.2008.01.003.
[39] Quarton CJ, Samsatli S. The value of hydrogen and carbon capture, storage and utilisation in decarbonising energy: insights from integrated value chain optimisation. Appl Energy 2020;257:113936. https://doi.org/10.1016/j.apenergy.2019.113936.
[40] Lara CL, Mallapragada DS, Papageorgiou DJ, Venkatesh A, Grossmann IE. Deterministic electric power infrastructure planning: mixed-integer programming model and nested decomposition algorithm. Eur J Oper Res 2018;271:1037–54. https://doi.org/10.1016/j.ejor.2018.05.039.
[41] Liu Z, Wang S, Ouyang Y. Reliable biomass supply chain design under feedstock seasonality and probabilistic facility disruptions. Energies 2017:10. https://doi.org/10.3390/en10111895.
[42] You F, Wang B. Life cycle optimization of biomass-to-liquid supply chains with distributed-centralized processing networks. Ind Eng Chem Res 2011;50: 10102–27. https://doi.org/10.1021/ie200850t.
[43] Quddus MA, Chowdhury S, Marufuzzaman M, Yu F, Bian L. A two-stage chance-constrained stochastic programming model for a bio-fuel supply chain network. Int J Prod Econ 2018;195:27–44. https://doi.org/10.1016/j.ijpe.2017.09.019.
[44] Fattahi M, Govindan K. A multi-stage stochastic program for the sustainable design of biofuel supply chain networks under biomass supply uncertainty and disruption risk: a real-life case study. Transp Res Part E Logist Transp Rev 2018; 118:534–67. https://doi.org/10.1016/j.tre.2018.08.008.
[45] Walther G, Schatka A, Spengler TS. Design of regional production networks for second generation synthetic bio-fuel – a case study in Northern Germany. Eur J Oper Res 2012;218:280–92. https://doi.org/10.1016/j.ejor.2011.09.050.
[46] Hombach LE, Büsing C, Walther G. Robust and sustainable supply chains under market uncertainties and different risk attitudes – a case study of the German biodiesel market. Eur J Oper Res 2018;269:302–12. https://doi.org/10.1016/j.ejor.2017.07.015.
[47] Osmani A, Zhang J. Stochastic optimization of a multi-feedstock lignocellulosic-based bioethanol supply chain under multiple uncertainties. Energy 2013;59: 157–72. https://doi.org/10.1016/j.energy.2013.07.043.
[48] Zhang J, Osmani A, Awudu I, Gonela V. An integrated optimization model for switchgrass-based bioethanol supply chain. Appl Energy 2013;102:1205–17. https://doi.org/10.1016/j.apenergy.2012.06.054.
[49] Hombach LE, Walther G. Pareto-efficient legal regulation of the (bio)fuel market using a bi-objective optimization model. Eur J Oper Res 2015;245:286–95. https://doi.org/10.1016/j.ejor.2015.02.039.
[50] Samsatli S, Samsatli NJ. A multi-objective MILP model for the design and operation of future integrated multi-vector energy networks capturing detailed spatio-temporal dependencies. Appl Energy 2018;220:893–920. https://doi.org/10.1016/j.apenergy.2017.09.055.
[51] Nguyen TH, Granger J, Pandya D, Paustian K. High-resolution multi-objective optimization of feedstock landscape design for hybrid first and second generation biorefineries. Appl Energy 2019;238:1484–96. https://doi.org/10.1016/j.apenergy.2019.01.117.
[52] Walker G. Energy, land use and renewables. A changing agenda. Land Use Policy 1995;12:3–6. https://doi.org/10.1016/0264-8377(95)90069-E.
[53] Bernardi A, Giarola S, Bezzo F. Spatially explicit multiobjective optimization for the strategic design of first and second generation biorefineries including carbon and water footprints. Ind Eng Chem Res 2013;52:7170–80. https://doi.org/10.1021/ie302442j.
[54] Kati V, Kassara C, Vrontisi Z, Moustakas A. The biodiversity-wind energy-land use nexus in a global biodiversity hotspot. Sci Total Environ 2021;768:144471. https://doi.org/10.1016/j.scitotenv.2020.144471.
[55] Dhar A, Naeth MA, Jennings PD, Gamal El-Din M. Perspectives on environmental impacts and a land reclamation strategy for solar and wind energy systems. Sci Total Environ 2020;718:134602. https://doi.org/10.1016/j.scitotenv.2019.134602.
[56] Ponitka J, Boettner S. Challenges of future energy landscapes in Germany – a nature conservation perspective. Energy Sustain Soc 2020;10:1–12. https://doi.org/10.1186/s13705-020-00250-9.
[57] Zhong J, Yu TE, Clark CD, English BC, Larson JA, Cheng CL. Effect of land use change for bioenergy production on feedstock cost and water quality. Appl Energy 2018;210:580–90. https://doi.org/10.1016/j.apenergy.2017.09.070.
[58] Samsatli S, Samsatli NJ, Shah N. BVCM: a comprehensive and flexible toolkit for whole system biomass value chain analysis and optimisation – mathematical formulation. Appl Energy 2015;147:131–60. https://doi.org/10.1016/j.apenergy.2015.01.078.
[59] Sitorus F, Brito-Parada PR. The selection of renewable energy technologies using a hybrid subjective and objective multiple criteria decision making method. Expert Syst Appl 2022;206:117839. https://doi.org/10.1016/j.eswa.2022.117839.
[60] Huang E, Zhang X, Rodriguez L, Khanna M, de Jong S, Ting KC, et al. Multi-objective optimization for sustainable renewable jet fuel production: a case study of corn Stover based supply chain system in Midwestern U.S. Renew Sustain Energy Rev 2019;115:109403. https://doi.org/10.1016/j.rser.2019.109403.
[61] Nonhebel S. Land-use changes induced by increased use of renewable energy sources. Glob Environ Chang L Use 2003;2020:187–202. https://doi.org/10.1007/978-94-017-0335-2_8.
[62] Laborde D, Valin H. Modeling land-use changes in a global CGE: assessing the eu biofuel mandates with the MIRAGE-biof model. Clim Chang Econ 2012:3. https://doi.org/10.1142/S2010007812500170.
[63] Subramaniam V, Kuntom A, Zainal H, Loh SK, Aziz AA, Parveez GKA. Analysis of the uncertainties of the inclusion of indirect land use change into the European Union renewable energy sources Directive II. J Oil Palm Res 2019;31:480–8. https://doi.org/10.21894/jopr.2019.0042.
[64] Cintas O, Berndes G, Englund O, Johnsson F. Geospatial supply-demand modeling of lignocellulosic biomass for electricity and biofuels in the European Union. Biomass Bioenergy 2021:144. https://doi.org/10.1016/j.biombioe.2020.105870.
[65] Hoogwijk M, Faaij A, de Vries B, Turkenburg W. Exploration of regional and global cost-supply curves of biomass energy from short-rotation crops at abandoned cropland and rest land under four IPCC SRES land-use scenarios. Biomass Bioenergy 2009;33:26–43. https://doi.org/10.1016/j.biombioe.2008.04.005.
[66] MacKay DJC. Solar energy in the context of energy use, energy transportation and energy storage. Philos Trans R Soc A Math Phys Eng Sci 2013:371. https://doi.org/10.1098/rsta.2011.0431.
[67] van de Ven DJ, Capellan-Peréz I, Arto I, Cazcarro I, de Castro C, Patel P, et al. The potential land requirements and related land use change emissions of solar energy. Sci Rep 2021;11:1–12. https://doi.org/10.1038/s41598-021-82042-5.
[68] García-Olivares Antonio. Energy for a sustainable post-carbon society Antonio. Sci Mar 2016;80:257–68. https://doi.org/10.3989/scimar.04295.12A.
[69] Teske S, Sawyer S, Schäfer O, Pregger T, Simon S, Naegler T. Energy [R]evolution – a sustainable world energy outlook 2015. 2015. p. 1–313. 1. doi:10.3726/978-3-653-05076-9.
[70] Jacobson MZ, Delucchi MA, Bazouin G, Bauer ZAF, Heavey CC, Fisher E, et al. 100% clean and renewable wind, water, and sunlight (WWS) all-sector energy roadmaps for the 50 United States. Energ Environ Sci 2015;8:2093–117. https://doi.org/10.1039/c5ee01283j.
[71] Cheng VKM, Hammond GP. Life-cycle energy densities and land-take requirements of various power generators: a UK perspective. J Energy Inst 2017; 90:201–13. https://doi.org/10.1016/j.joei.2016.02.003.
[72] Garcia DJ, You F. Addressing global environmental impacts including land use change in life cycle optimization: studies on biofuels. J Clean Prod 2018;182: 313–30. https://doi.org/10.1016/j.jclepro.2018.02.012.

[73] Sliz-Szkliniarz B. Assessment of the renewable energy-mix and land use trade-off at a regional level: a case study for the Kujawsko-Pomorskie Voivodship. Land Use Policy 2013;35:257–70. https://doi.org/10.1016/j.landusepol.2013.05.018.
[74] Nazari A, Penazzi S, Ernst AT, Dunstall S, Bryan B, Connor J, et al. An integrated model of land-use trade-offs and expanding agricultural processing centres. In: Proc - 21st Int Congr model simulation, MODSIM 2015; 2015. p. 1219–25.
[75] Fthenakis V, Kim HC. Land use and electricity generation: a life-cycle analysis. Renew Sustain Energy Rev 2009;13:1465–74. https://doi.org/10.1016/j.rser.2008.09.017.
[76] Guo M, Richter GM, Holland RA, Eigenbrod F, Taylor G, Shah N. Implementing land-use and ecosystem service effects into an integrated bioenergy value chain optimisation framework. Comput Chem Eng 2016;91:392–406. https://doi.org/10.1016/j.compchemeng.2016.02.011.
[77] Trondle T. Supply-side options to reduce land requirements of fully renewable electricity in Europe. PloS One 2020;15:1–19. https://doi.org/10.1371/journal.pone.0236958.
[78] Zhang C, Li Z, Jiang H, Luo Y, Xu S. Deep learning method for evaluating photovoltaic potential of urban land-use: a case study of Wuhan. China Appl Energy 2021;283:116329. https://doi.org/10.1016/j.apenergy.2020.116329.
[79] Drews M, Larsen MAD, Peña Balderrama JG. Projected water usage and land-use-change emissions from biomass production (2015–2050). Energ Strat Rev 2020:29. https://doi.org/10.1016/j.esr.2020.100487.
[80] Yimam YT, Ochsner TE, Kakani VG. Evapotranspiration partitioning and water use efficiency of switchgrass and biomass sorghum managed for biofuel. Agric Water Manag 2015;155:40–7. https://doi.org/10.1016/j.agwat.2015.03.018.
[81] Hamilton SK, Hussain MZ, Bhardwaj AK, Basso B, Robertson GP. Comparative water use by maize, perennial crops, restored prairie, and poplar trees in the US Midwest. Environ Res Lett 2015;10:64015. https://doi.org/10.1088/1748-9326/10/6/064015.
[82] Gerbens-Leenes PW, Hoekstra AY, van der Meer TH. Water footprint of bio-energy and other primary energy carriers. Value 2008;29:44.
[83] Gerbens-Leenes PW, Hoekstra AY, van der Meer T. The water footprint of energy from biomass: a quantitative assessment and consequences of an increasing share of bio-energy in energy supply. Ecol Econ 2009;68:1052–60. https://doi.org/10.1016/j.ecolecon.2008.07.013.
[84] Simoes SG, Catarino J, Picado A, Lopes T. Assessing water availability and use for electrolysis in hydrogen production. 2021. https://doi.org/10.13140/RG.2.2.18531.27685.
[85] Dincer I, Acar C. Review and evaluation of hydrogen production methods for better sustainability. Int J Hydrogen Energy 2014;40:11094–111. https://doi.org/10.1016/j.ijhydene.2014.12.035.
[86] Turner JA. Sustainable hydrogen production. Science (80-) 2004;305:972–4. https://doi.org/10.1126/science.1103197.
[87] Lee U, Xu H, Daystar J, Elgowainy A, Wang M. AWARE-US: quantifying water stress impacts of energy systems in the United States. Sci Total Environ 2019;648:1313–22. https://doi.org/10.1016/j.scitotenv.2018.08.250.
[88] Mehmeti A, Angelis-Dimakis A, Arampatzis G, McPhail SJ, Ulgiati S. Life cycle assessment and water footprint of hydrogen production methods: from conventional to emerging technologies. Environ - MDPI 2018;5:1–19. https://doi.org/10.3390/environments5020024.
[89] Kallrath J. Mixed integer optimization in the chemical process industry: experience, potential and future perspectives. Chem Eng Res Des 2000;78:809–22. https://doi.org/10.1205/026387600528012.
[90] Smil V. Power density primer: understanding the spatial dimension of the unfolding transition to renewable electricity generation (Part I – definitions). Retrieved June26; 2010. p. 2019.
[91] Fischer RA. Definitions and determination of crop yield, yield gaps, and of rates of change. F Crop Res 2015;182:9–18. https://doi.org/10.1016/j.fcr.2014.12.006.
[92] Hoekstra AY, Hung PQ. Virtual water trade: a quantification of virtual water flows between nations in relation to international crop trade. Value of. Water Research Report Series 11. Delft, Delft, Netherlands: IHE; 2002. https://www.waterfootprint.org/resources/Report11.pdf.
[93] Cintas O, Berndes G, Englund O, Cutz L, Johnsson F. Geospatial supply–demand modeling of biomass residues for co-firing in European coal power plants. GCB Bioenergy 2018;10:786–803. https://doi.org/10.1111/gcbb.12532.
[94] Khorram E, Khaledian K, Khaledyan M. A numerical method for constructing the Pareto front of multi-objective optimization problems. J Comput Appl Math 2014;261:158–71. https://doi.org/10.1016/j.cam.2013.11.007.
[95] Mavrotas G. Effective implementation of the ε-constraint method in multi-objective mathematical programming problems. Appl Math Comput 2009;213:455–65. https://doi.org/10.1016/j.amc.2009.03.037.
[96] Aghaei J, Amjady N, Shayanfar HA. Multi-objective electricity market clearing considering dynamic security by lexicographic optimization and augmented epsilon constraint method. Appl Soft Comput J 2011;11:3846–58. https://doi.org/10.1016/j.asoc.2011.02.022.
[97] Du Y, Xie L, Liu J, Wang Y, Xu Y, Wang S. Multi-objective optimization of reverse osmosis networks by lexicographic optimization and augmented epsilon constraint method. Desalination 2014;333:66–81. https://doi.org/10.1016/j.desal.2013.10.028.
[98] Nezhad AE, Javadi MS, Rahimi E. Applying augmented É-constraint approach and lexicographic optimization to solve multi-objective hydrothermal generation scheduling considering the impacts of pumped-storage units. Int J Electr Power Energy Syst 2014;55:195–204. https://doi.org/10.1016/j.ijepes.2013.09.006.
[99] Razmi J, Zahedi-Anaraki AH, Zakerinia MS. A bi-objective stochastic optimization model for reliable warehouse network redesign. Math Comput Model 2013;58:1804–13. https://doi.org/10.1016/j.mcm.2013.03.009.
[100] Zhang W, Reimann M. A simple augmented ∈−constraint method for multi-objective mathematical integer programming problems. Eur J Oper Res 2014;234:15–24. https://doi.org/10.1016/j.ejor.2013.09.001.
[101] Mavrotas G, Florios K. An improved version of the augmented s-constraint method (AUGMECON2) for finding the exact pareto set in multi-objective integer programming problems. Appl Math Comput 2013;219:9652–69. https://doi.org/10.1016/j.amc.2013.03.002.
[102] Larson ED, Jin H, Celik FE. Large-scale gasification-based coproduction of fuels and electricity from switchgrass. Biofuels Bioprod Biorefin 2009;3:174–94. https://doi.org/10.1002/bbb.137.
[103] European Environment Agency. Water use in Europe — Quantity and quality face big challenges. 2018. p. 1–10. https://www.eea.europa.eu/signals/signals-2018-content-list/articles/water-use-in-europe-2014 (accessed February 27, 2023).
[104] Siegemund Stefan, Trommler Marcus, Zinnecker Valentin, Schmidt Patrick, Weindorf Werner, Zittel Werner, et al. E-fuels study. 2017. p. 1–175.
[105] Ruiz P, Nijs W, Tarvydas D, Sgobbi A, Zucker A, Pilli R, et al. ENSPRESO - an open, EU-28 wide, transparent and coherent database of wind, solar and biomass energy potentials. Energ Strat Rev 2019;26:100379. https://doi.org/10.1016/j.esr.2019.100379.
[106] Haase M, Rösch C, Ketzer D. GIS-based assessment of sustainable crop residue potentials in European regions. Biomass Bioenergy 2016;86:156–71. https://doi.org/10.1016/j.biombioe.2016.01.020.
[107] European Commission E. Water resources: long-term annual average 2022. https://data.europa.eu/data/datasets/ocghud9lo16m1j9flj9ba?locale=en; 2022 (accessed November 20, 2022).
[108] Report F. Zukünftige Kraftstoffe: FVV-Kraftstoffstudie IV Future Fuels: FVV Fuels Study IV Transformation der Mobilität im klimaneutralen und postfossilen Zeitalter. 2021.
[109] DNV GL. Study on the import of liquid renewable energy: technology cost assessment. [Online]. 2020. Available: https://www.gie.eu/wp-content/uploads/filr/2598/DNV-GL_Study-GLE-Technologies-and-costs-analysis-on-imports-of-liquid-renewable-energy.pdf.
[110] Fasihi M, Efimova O, Breyer C. Techno-economic assessment of CO 2 direct air capture plants. J Clean Prod 2019;224:957–80. https://doi.org/10.1016/j.jclepro.2019.03.086.
[111] Mccollum DL, Ogden JM. Techno-economic models for carbon dioxide compression, transport, and storage. Davis: Univ California; 2006.
[112] Wang A, van der Leun K, Peters D, Buseman M. European Hydrogen Backbone. https://transparency.entsog.eu/.
[113] van Zalk J, Behrens P. The spatial extent of renewable and non-renewable power generation: a review and meta-analysis of power densities and their application in the U.S. Energy Policy 2018;123:83–91. https://doi.org/10.1016/j.enpol.2018.08.023.
[114] International renewable energy agency (IRENA). Innovation outlook: Renewable Mini-grids. 2016.
[115] Alvarado M. The changing face of the global methanol industry. IHS Chem Bull 2016:10–1.
[116] (NCDC) NC for DC. 2020 edition. 2020.
[117] Brynolf S, Taljegard M, Grahn M, Hansson J. Electrofuels for the transport sector: a review of production costs. Renew Sustain Energy Rev 2018;81:1887–905. https://doi.org/10.1016/j.rser.2017.05.288.
[118] Searle S, Christensen A. Decarbonization potential of Electrofuels in the European Union. Washington, DC, USA: The International Council on Clean Transportation; 2018. https://theicct.org/sites/default/files/publications/Electrofuels_Decarb.
[119] European Commission JRC. ENSPRESO - BIOMASS. http://data.europa.eu/89h/74ed5a04-7d74-4807-9eab-b94774309d9f; 2019.
[120] European Commission JRC. ENSPRESO - SOLAR - PV and CSP. http://data.europa.eu/89h/18eb348b-1420-46b6-978a-fe0b79e30ad3; 2019.
[121] European Commission JRC. ENSPRESO - WIND - ONSHORE and OFFSHORE. http://data.europa.eu/89h/6d0774ec-4fe5-4ca3-8564-626f4927744e; 2019.
[122] Reuß M, Grube T, Robinius M, Preuster P, Wasserscheid P, Stolten D. Seasonal storage and alternative carriers: a flexible hydrogen supply chain model. Appl Energy 2017;200:290–302. https://doi.org/10.1016/j.apenergy.2017.05.050.
[123] Akhtari S, Sowlati T, Griess VC. Integrated strategic and tactical optimization of forest-based biomass supply chains to consider medium-term supply and demand variations. Appl Energy 2018;213:626–38. https://doi.org/10.1016/j.apenergy.2017.10.017.
[124] Wang A, Van der Leun K, Peters D, Buseman M. European hydrogen backbone 2020:24.
[125] Xie F, Huang Y, Eksioglu S. Integrating multimodal transport into cellulosic biofuel supply chain design under feedstock seasonality with a case study based on California. Bioresour Technol 2014;152:15–23. https://doi.org/10.1016/j.biortech.2013.10.074.
[126] Leduc S. Development of an optimization model for the location of biofuel production plants. 2009.
[127] Wolter C. Technology catalogue for transport of energy. https://ens.dk/en/our-services/projections-and-models/technology-data/technology-catalogue-transport-energy; 2021.
[128] Varone A, Ferrari M. Power to liquid and power to gas: an option for the German Energiewende. Renew Sustain Energy Rev 2015;45:207–18. https://doi.org/10.1016/j.rser.2015.01.049.