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Research article

Towards CO_2 valorization in a multi remote renewable energy hub framework with uncertainty quantification

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ABSTRACT

In this paper, we propose a multi-RREH (Remote Renewable Energy Hub) based optimization framework. This framework allows a valorization of CO_2 using carbon capture technologies. This valorization is grounded on the idea that CO_2 gathered from the atmosphere or post combustion can be combined with hydrogen to produce synthetic methane. The hydrogen is obtained from water electrolysis using renewable energy. Such renewable energy is generated in RREH, which are locations where RE is cheap and abundant (e.g., solar PV in the Sahara Desert, or wind in Greenland). We instantiate our framework on a case study focusing on Belgium and 2 RREH, and we conduct a techno-economic analysis under uncertainty. This analysis highlights, among others, the interest in capturing CO_2 via Post Combustion Carbon Capture (PCCC) rather than only through Direct Air Capture (DAC) for methane synthesis in RREH. By doing so, a notable reduction of 10% is observed in the total cost of the system under our reference scenario. In addition, we use our framework to derive a carbon price threshold above which carbon capture technologies may start playing a pivotal role in the decarbonation process of our industries.

1. Introduction

While the whole world is engaged in a process to decrease greenhouse gas emissions, capturing CO_2 appears more and more as a crucial element to limit global warming. Once it is captured, CO_2 may be either stored (CCS — Carbon Capture and Storage), or valorized (CCU — Carbon Capture and Utilization), for instance, through synthetic methane generation. In this article, we focus on CCU, where CO_2 is seen as a required ingredient in the process of generating synthetic methane, together with *green* hydrogen, i.e. hydrogen obtained from renewable energy-based electrolysis. This work is mainly related to the following topics that may play an important role in the deep decarbonization of our societies: (i) global grid approaches, (ii) power-to-X technologies, multi-energy systems and energy hub approaches, and (iii) CO_2 quotas markets.

Global Grid approaches (Chatzivasileiadis et al., 2013; Yu et al., 2019), sometimes referred to as Global Energy Interconnection approaches (Liu, 2015), are related to the idea of harvesting renewable energy from abundant and potentially remote renewable energy fields to feed the electricity demand in high demand centers. These approaches have mainly been oriented towards solutions using the electricity vector to repatriate energy from energy hubs, and have received a growing interest starting from the DESERTEC concept (Samus et al., 2013) that focuses on Sahara solar energy resources from the Sahara desert to serve the European electricity demand. More recently, wind from Northern Europe and Greenland has also been identified as a promising resource to be valued within the Global Grid context (Radu et al., 2022). Resource and demand configurations combining several types of resources as well as demand time zones show better results (Yu et al., 2019).

Multi-energy systems approaches (Munster et al., 2020; O'Malley et al., 2016) exploit the benefits of integrating energy demand and generation, as well as infrastructure. Power-to-X technologies, in particular power-to-CH4 technologies using hydrolysis and renewable energy for producing H2 (Götz et al., 2016), offer a CO_2 neutral solution to serve gas demand, but also a way to store vast quantities of energy issues from renewable sources (Blanco and Faaij, 2018). Recently, Berger et al. have proposed a modeling framework (Berger et al., 2021) for assessing the techno-economics viability of carbon-neutral

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synthetic fuel production from renewable electricity in remote areas where high-quality renewable resources are abundant. Let us mention that the idea of energy hubs was preexisting the work of Geidl et al. (2006), Mohammadi et al. (2017) and Sadeghi et al. (2019), however, the contribution of Berger et al. is the introduction of remote energy production, far from the demand as well as the modeling and optimization of the entire supply chains. More recently, Pfennig et al. (2023) conducted a techno-economic analysis of numerous regions worldwide for the production of synthetic fuels. Additionally, Hampp et al. (2023) performed an analysis presenting various import options of hydrogen-based molecules in Germany. However, these two recent studies only consider sourcing CO_2 from Direct Air Capture (DAC) and did not consider another way for sourcing the CO_2. Moreover, Greenland was not considered as a potential hub in their analyses.

As in our previous work (Dachet et al., 2023) from which this paper is an extended version, we build on top of the Remote Renewable Energy Hub (RREH) approach (Berger et al., 2021) to propose a multi-hub, multi CO_2 sources approach. CO_2 is captured using both Post-Combustion Carbon Capture (PCCC) and Direct Air Capture (DAC) technologies. Hydrogen is produced from electrolysis using renewable energy in a RREH, which is particularly well-suited for producing cheap and abundant renewable energy (e.g., solar energy in the Sahara desert, or wind energy in Greenland). The RREH concept also relies on the following idea: some locations show large amounts of energy consumption while not having lots of renewable energy resources (e.g., Belgium). Conversely, some places have abundant renewable energy and almost no energy demand. In its original formulation (Berger et al., 2021), the RREH concept suggests using DAC technologies to feed the CO_2 demand at the RREH. In this paper, we include PCCC technologies as an alternative to DAC technologies: in addition or replacement to being captured in the atmosphere, CO_2 emitted in energy-intensive locations may be transported to the RREH to be combined with green hydrogen for producing neutral synthetic methane.

The main contributions of this work are as follows:

- We introduce a loop of CO_2 from the importer of gas to the RREH;
- We model and optimize the entire supply chain to meet the energy demand of Belgium in 2050, considering gas and electricity at an hourly resolution with two RREHs;
- We consider a new potential RREH located in Greenland;
- We provide a detailed techno-economic analysis by scenarios and considering uncertainty for one of them.

2. Scope of the study

We propose a methodology for assessing the techno-economic feasibility of exporting CO_2 into RREH where synthetic CO_2-neutral methane would be generated using locally produced green H2. We formalize an optimization problem where CO_2 sources are in “competition” to provide CO_2 to the methanation units in the RREH. This methodology is based on a linear program modeling of Belgium’s energy system, including gas and electricity demand, main CO_2 emitters and two RREH namely Greenland and Algeria. We rely on previously published approaches to develop our approach (Berger et al., 2021), and, in particular, we use the GBOML language (Miftari et al., 2022) to model the energy system and to optimize it.

This work, aiming to enhance the value of CO_2, closely aligns with various policy mechanisms implementing a price on CO_2 emissions. These include a carbon tax or participation in carbon markets like the European Union Emissions Trading System (EU ETS)[1] Indeed, the business model of the proposed model is strengthened by these mechanisms because we propose to recycle the CO_2 emitted in the atmosphere (or that could be emitted) rather than paying for it.

On top of the energy system optimization methodology, an uncertainty quantification (UQ) analysis can be performed. Indeed, many technical and economic parameters of the energy system model can influence the system performance, which are often subject to uncertainty due to lack of knowledge (i.e., epistemic uncertainty) or unknown future evolution of the parameters (i.e., aleatory uncertainty) (Coppitters and Contino, 2023).

Several methods exist to characterize parametric uncertainties in the context of energy systems (Mavromatidis et al., 2018), including, among others, interval analysis, fuzzy set theory and Probability Density Functions (PDFs) (Dubois, 2023). In the case of PDFs, the distributions are derived through statistical inference when a lot of data is available, expert judgment in the absence of data, or Bayesian inference when the dataset is limited but expert knowledge is accessible (Nadimi and Tokimatsu, 2017).

When input parameters are characterized by distributions and propagated through the system model, the model outputs will also be defined by distributions. Therefore analyses of these output distributions can be performed. In this paper, we used a probabilistic approach technique, called Polynomial Chaos Expansion (PCE). This technique acts mainly as a surrogate for Monte Carlo (MC) simulation allowing to derive statistical moments of output distributions given known (or assumed) input distributions. Moreover, this technique offers a distinct advantage over other surrogate methods (Kriging (Deng et al., 2020), support vector machines (Cai et al., 2023), Analysis Of Variance (ANOVA) (Gradov et al., 2022)) by enabling the analytical derivation of global sensitivity indices. These indices allow a decomposition of the variance of the output distribution with respect to the given input parameters.

PCE has already been applied with success in Rixhon et al. (2021) for quantifying the uncertainty associated with the total energy cost of the Belgian energy system, considering 43 uncertain input parameters related to the investment and operating cost of the available technologies. Furthermore, their analysis identified the cost of importing electrofuels as the primary driver of the variance in the total system cost using the analytically-derived global sensitivity indices.

3. CO_2 valorization in a multi-remote renewable energy hubs approach

The Remote Renewable Energy Hub concept was first introduced in Berger et al. (2021), where the authors proposed a hub for synthesizing CH4 based on hydrogen and CO2 captured from the air thanks to a methanation unit. This concept has emerged within the context of global grid (Chatzivasileiadis et al., 2013) and multi-energy systems approaches. These approaches aim at optimizing the generation and utilization of renewable energy (RE) by both (i) looking for abundant and cheap RE fields, (ii) taking advantage of daily/seasonal complementary of RE, and (iii) using power-to-gas technologies for better addressing RE generation fluctuations and meet e-fuels demand to act as a substitute for molecules derived nowadays from fossil fuels.

In the original article (Berger et al., 2021), the methanation unit was supplied with CO_2 by a Direct Air Capture unit, and the energy demand was fulfilled by a single RREH located in Algeria. However, in this paper, we propose to investigate the feasibility of valorizing CO_2 captured through Post Combustion Capture techniques at the energy demand center. Additionally, we deviate from the original paper by introducing a multi-RREH approach, wherein the energy demand center serves as a CO_2 provider to a set of multiple RREH, denoted as $RREH_1, \ldots, RREH_h$. Each hub $RREH_i (1 \leq i \leq h)$ has its unique characteristics, such as renewable energy type, potential, distance from the energy demand center, and means of CO_2 transport from the energy demand center, which can affect its competitiveness.

[1] The EU ETS system is described on the European Commission’s website: https://climate.ec.europa.eu/eu-action/eu-emissions-trading-system-eu-ets_en and in Brohé et al. (2009).

In order to illustrate the concepts discussed above, we have developed a model for a multi-RREH system based on the following assumptions: (i) the energy demand center is Belgium, encompassing its gas and electricity demands as well as its CO_2 emissions, (ii) there are two RREH: one situated in the Sahara desert with access to solar and wind resources, and another in Greenland benefiting from the high-quality wind fields in the region. A detailed schematic of the resulting system is shown in Fig. 1.

We note that the model code with two RREH and one energy demand center system is available online[2] and can be easily extended to add additional RREH and energy demand centers.

4. Modeling

In this section we describe the optimization problem underlying our techno-economic analysis and we describe mathematically the UQ quantification and sensitivity analysis.

4.1. Multi-energy system model optimization

This subsection provides insight into the optimization framework that underlies the multi-energy system model proposed in this work. The GBOML language, introduced in Miftari et al. (2022), a recently developed language dedicated to the modeling of complex systems exhibiting a graph structure, as multi-energy systems do, will be utilized. GBOML exhibits several advantages; it is open source, easy to use, and allows the construction of a sparse matrix representation of the system.

The optimization problem can be viewed as an optimization on graphs, where a multi-energy system is considered as a set of nodes $\mathcal{N}$ that contribute to the (linear) objective and local constraints, and hyperedges $\mathcal{E}$ are used to model the constraints between nodes, such as those between RREH and the energy demand center in our context.

The formalism utilized in this study follows the framework introduced in Berger et al. (2021). The entire system is defined by sets of nodes $\mathcal{N}$ and hyperedges $\mathcal{E}$. The optimization horizon is denoted by T, with time-steps indexed by $t \in \mathcal{T}$, where $\mathcal{T} = \{1, \dots, T\}$.

A node $n \in \mathcal{N}$ is defined by internal X^n and external Z^n variables, where internal variables describe the specific characteristics of the unit, such as the nominal power capacity installed in the asset. Equality constraints $h_i(X^n, Z^n, t) = 0$ with $i \in \mathcal{I}$ and inequality constraints $g_j(X^n, Z^n, t) \leq 0$ with $j \in \mathcal{J}$, are employed for each $t \in \mathcal{T}$ to model operational constraints.

Each node n has an associated cost function $F^n(X^n, Z^n) = f^n(X^n, Z^n, 0) + \sum_{t=1}^{T} f^n(X^n, Z^n, t)$ that typically represents the capital expenditure and operational expenditure, i.e., CAPEX and OPEX, respectively.

Finally, equality and inequality constraints on hyperedges can be defined as $H^e(Z^e) = 0$ and $G^e(Z^e) \leq 0$ with $e \in \mathcal{E}$ to model the laws of conservation and caps on given commodities.

One can read this type of problem as:

$$\begin{aligned} \min \quad & \sum_{n=1}^{N} F^n(X^n, Z^n) \\ \text{s.t.} \quad & h_i(X^n, Z^n, t) = 0, \forall n \in \mathcal{N}, \forall t \in \mathcal{T}, \forall i \in \mathcal{I} \\ & g_j(X^n, Z^n, t) \leq 0, \forall n \in \mathcal{N}, \forall t \in \mathcal{T}, \forall j \in \mathcal{J} \\ & H^e(Z^e) = 0, \forall e \in \mathcal{E} \\ & G^e(Z^e) \leq 0, \forall e \in \mathcal{E}. \end{aligned} \tag{1}$$

The main assumptions underlying our model are the following:

- Centralized planning and operation: In this framework, a single entity is responsible for making all investment and operation decisions.
- Perfect forecast and knowledge: It is assumed that the demand curves, as well as weather time series, are available and known *in advance* for the entire optimization horizon, i.e., $\forall t \in \{1, \dots, T\}$.
- Permanence of investment decisions: Investment decisions result in the sizing of installation capacities at the beginning of the time horizon. Capacities remain fixed throughout the entire optimization period, i.e., $\forall t \in \{1, \dots, T\}$.
- Linear modeling of technologies: All technologies and their interactions are modeled using linear equations within this framework.
- Spatial aggregation: The energy demands and generation at each node are represented by single points. The topology of the embedded network required to serve this demand locally is not modeled in this approach. This can be viewed as an extension of the copper plate modeling approach used in electrical power systems.

In our problem, all cost functions and constraints are affine transformations of the inputs. More details on the constraints of each technology can be found in Berger et al. (2020, 2021). Additionally, the local objective function corresponding to the CAPEX is modeled with a uniform weighted average cost of capital (WACC) of 7% for each technology. Let L_n denote the lifetime of technology n and w the WACC. Then, the annual cost $zeta^n$ of investing in technology n writes:

$$\zeta^n = \text{CAPEX}_n \times \frac{\mathrm{w}}{(1 - (1 + \mathrm{w})^{-\mathrm{L}_n})}. \tag{2}$$

Moreover, a cap on the net CO_2 emissions (*i.e.* release in minus captured from the atmosphere) is added to the model. This latter is defined as

$$\sum_{t \in \mathcal{T}} \left(\sum_{a \in \mathcal{A}} q^a_{co2,t} - \sum_{c \in C} q^c_{co2,t} \right) \leq \kappa_{co2} \nu \tag{3}$$

with $\mathcal{A}$ and C representing the sets of technologies that release CO_2 into the atmosphere and those that capture CO_2 directly from the atmosphere, respectively, κ_{co2} represents the CO_2 cap in kilotons per year, and ν represents the number of years covered by the optimization horizon. The shadow price, or marginal cost, which is the dual variable associated with Eq. (3) allows for the derivation of a CO_2 cost in €/t. Nevertheless, one should be cautious with the derived shadow prices, as they provide information that is relevant within the context of the model and the various constraints taken into account. A detailed explanation of dual variables as marginal costs in linear programming can be found in Bertsimas and Tsitsiklis (1997, Chapter 4).

Finally, GBOML is a convenient tool for modeling the nodes and hyperedges of the optimization problem we described. In the RREH context, the nodes represent all the units composing the RREH, and the hyperedges represent the flows between the units. Moreover, GBOML allows the definition of constraints and objective functions for each node. The readiness of GBOML makes it easy to understand the complex system described by simply reading the code. As an illustration, readers can gain insight into Fig. 1 by comparing it with its GBOML implementation, accessible at https://gitlab.uliege.be/smart_grids/public/gboml/-/tree/master/examples, to observe its readiness.

4.2. Uncertainty quantification

The optimization problem outlined in Section 4.1 is defined by several economic parameters that are subject to uncertainty, either due to a lack of knowledge or due to the unknown future evolution of these parameters (Coppitters and Contino, 2023). The optimization problem $\mathcal{M}$ depending on such random parameters can be defined as a function:

$$\mathcal{M} : \mathbb{R}^M \to \mathbb{R}, \tag{4}$$

with M equal to the number of random parameters considered. The joint distribution of the random vector $\boldsymbol{X}$ of the random input parameters $\{X_i, i = 1, \dots, M\}$ can be defined as:

$$P_{\boldsymbol{X}}(\boldsymbol{x}) = \prod_{i=1}^{M} P_{X_i}(x_i), \qquad x_i \in \mathcal{D}_{X_i}, \tag{5}$$

[2] https://gitlab.uliege.be/smart_grids/public/gboml/-/tree/master/examples.

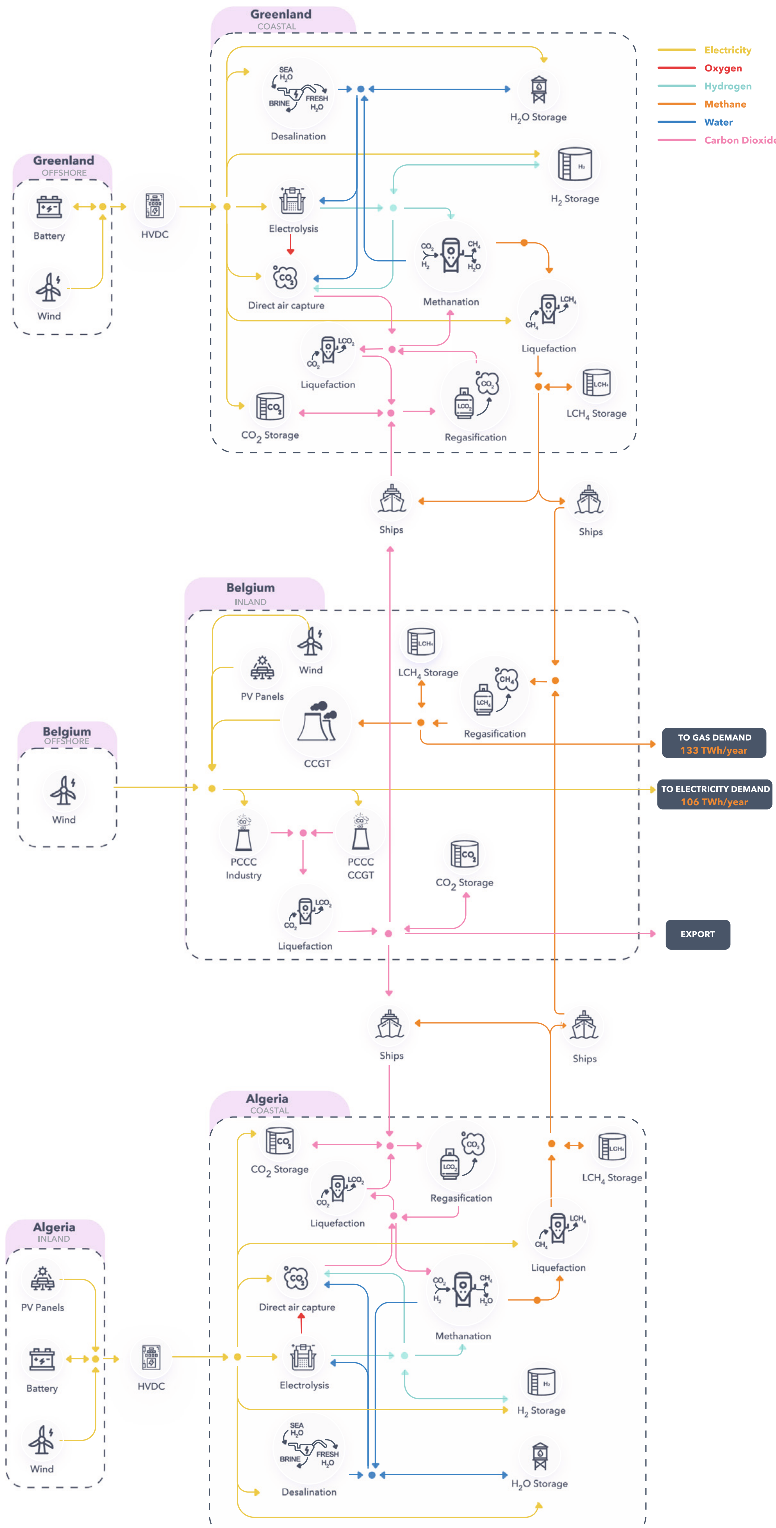

Fig. 1. A schematic illustration of the remote energy hub. CO_2 being captured, it may be used to synthesize fuel either locally either in a remote energy hub where renewable energy may be cheaper and more abundant.

where P_X is the joint distribution, $\left\{P_{X_i}\right\}_{i=1}^{M}$ are the marginal uniform distributions on the model input parameters (illustrated in Table 1) and $\mathcal{D}_{X_i}$ is the support of X_i.

As the input parameters are defined by a joint distribution, the output parameter of the model will become a random variable as well:

$$Y = \mathcal{M}(\boldsymbol{X}). \tag{6}$$

In this Uncertainty Quantification (UQ) procedure, the goal is to define the mean and standard deviation of the model output, to indicate the expected performance and the variability of the model output with respect to the random input parameters.

In addition, we will perform a global sensitivity analysis to quantify which random input parameters drive the variability of the model output. As this variability can be described by the variance of Y, the task is to allocate $\mathrm{Var}[Y]$ to each input parameter X_i. To do so, the Sobol' indices are adopted, corresponding to:

$$S_i = \frac{\mathrm{Var}\left[\mathcal{M}_i\left(X_i\right)\right]}{\mathrm{Var}\left[Y\right]} \tag{7}$$

where $\mathcal{M}_i\left(X_i\right) = \mathbb{E}\left[\mathcal{M}(\boldsymbol{X})\,|\,X_i\right] - \mathbb{E}\left[\mathcal{M}(\boldsymbol{X})\right]$.

To determine the mean, standard deviation and Sobol' indices on the output of the model, we used PCE. After the construction of the PCE surrogate model, it allows to derive the mean, standard deviation and Sobol' indices analytically. We utilized the open-source Python framework Rheia (Coppitters et al., 2022), which allows for easy computation of the PCE as well as analysis of the results. We refer to Sudret (2014) for the details on the construction of the PCE and the analytical derivation of the mean, standard deviation and Sobol' indices.

Using the methodology described in Sudret (2014), we constructed the PCE using 56 training samples, sampled from the joint input distribution using quasi-random Sobol sampling, resulting in a Leave-One-Out (LOO) cross-validation error below 1% (Sudret, 2014). The process of constructing a PCE has been repeated three times, once for every output of interest, namely total cost, shadow price, and cost of methane. Note that, as for each training sample, the model response for the three outputs of interest is stored, the same set of training samples was reused for the construction of each PCE.

5. Case study: Belgium

This case study is focused on Belgium with two remote renewable energy hubs: one located in Algeria and another one located in Greenland. We will analyze the techno-economic feasibility of the system while responding to an energy demand composed only of electricity and gas in Belgium.

5.1. Data

The data covers two years, 2015 and 2016, at an hourly resolution, which is necessary to capture the short-term variability of renewable energy production and demand. This granularity is essential for effective energy management and planning (Poncelet et al., 2016). However, real-time system operation requires minute-level resolution for management, which would demand significant computational resources for planning and control over long periods (years). The data have been retrieved from different sources (Berger et al., 2020, 2021). The renewable energy profiles for Greenland have been specifically produced for use in this study.

Renewable generation profiles

In order to determine the generation profiles of variable energy sources in Belgium we use the data from the transmission system operator (TSO) of Belgium (Elia, 2022b). The profiles for the RREH located in Algeria are extracted with the same methodology as in Berger et al. (2021). For the RREH situated in Greenland, the profiles of renewable energy are extracted thanks to the MAR model (Xavier et al., 2017) and given a power curve for an offshore wind turbine MHI Vestas Offshore V164-9.5 MW.

Table 1
The selected uncertain parameters are all the CAPEX related to the CO_2 infrastructure. A uniform distribution has been assumed for each parameter, with a ±30% variation for emerging technologies and a ±10% variation for mature technologies.

Parameters of the uniform distributions on the CO2 capex costs				
Name	Variation	min	max	Unit
$\mathrm{CAPEX}_{\mathrm{PCCC}}$	±30%	2205	4095	M€/kt/h
$\mathrm{CAPEX}_{\mathrm{CO_2,\ liq}}$	±10%	50.2	61.4	M€/kt/h
$\mathrm{CAPEX}_{\mathrm{CO_2,\ regas}}$	±10%	22.6	27.6	M€/kt/h
$\mathrm{CAPEX}_{\mathrm{CO_2,\ carrier}}$	±10%	4.5	5.5	M€/kt
$\mathrm{CAPEX}_{\mathrm{DAC}}$	±30%	3361	6242	M€/kt/h
$\mathrm{CAPEX}_{\mathrm{CO_2,\ liq\ storage}}$	±10%	2.1	2.5	M€/kt

Energy consumption

The energy consumption data is collected for two energy vectors: gas (from the gas system operator of Belgium, Fluxys (2022)) and electricity (from the TSO of Belgium, Elia (2022a)) with the same methodology as in Berger et al. (2020). In Fig. 2, the data corresponding to the two years is represented, where the signal is aggregated daily. In some cases, gas usage is shifted towards electricity needs, as described in Berger et al. (2020, section 4.2.2). This shift is due to the use of heat pumps, which can help decarbonize heating in Europe. For both energy vectors, industrial and heating demands are taken into account.

The peak power demand is equal to 60.13 GWh/h for both gas and electricity. The energy demand for electricity ranges from 6.42 to 20.29 GWh/h, while that for gas ranges from 5.51 to 39.84 GWh/h. The total energy demand is on average 106.45 TWh/year and 132.65 TWh/year for electricity and gas, respectively.

Uncertainty characterization

The CAPEX are influenced by various uncertainties, such as the evolving and maturing of technologies, the time gap between feasibility study and investment, and unexpected costs (Mavromatidis et al., 2018). These uncertainties can significantly impact the CAPEX assumptions during the optimization, leading to notable disparities between a deterministic assessment (based on the best estimate) and the real-world results. Consequently, we introduced uncertainty in the CAPEX for CO_2 processing technologies, with more substantial variations for emerging technologies (±30%) and narrower variations for mature technologies (±10%), following the approach proposed by Moret et al. (2017). The specific uncertain parameters are detailed in Table 1.

5.2. Model configuration

Our model consists of three main components (see Fig. 1): the energy demand center located in Belgium and two Remote Renewable Energy Hubs (RREH) situated in Algeria and Greenland. The RREH in Algeria is modeled as described in Berger et al. (2021) with the same techno-economic parameters. The distinction is made with the inclusion of the CO_2 connection between Belgium and Algeria. The RREH in Greenland is similarly modeled, with the exception of the removal of the photovoltaic potential and the modification of the high-voltage direct current (HVDC) line to a length of 100 km rather than 1000 km.

The transportation of CO_2 is achieved through the use of boats, which have a CAPEX of 5 M€/kt, a lifespan of 40 years, and an average daily energy consumption of 0.0150 GWh/day. CO_2 transport data was obtained from Danish Energy Agency (2023). The loading and traveling time for these boats are assumed identical to those for liquefied methane carriers (Berger et al., 2021), *i.e.* 24 and 116 h, respectively. In order to fill the tank of CO_2 carriers with fuel (liquefied methane), these tanks are loaded when unloading the CO_2 at the RREH. Indeed, at the RREH, synthetic CH4 is available without having undergone any additional transport-related losses.

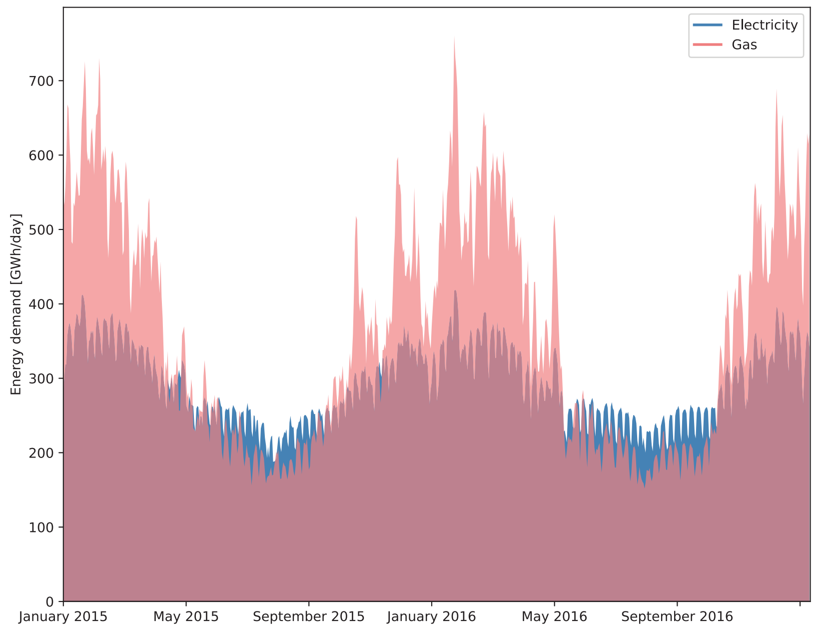

Fig. 2. Daily aggregated profiles of electricity and natural gas demand covering the years 2015 and 2016 spanned by the optimization.

A CO_2 liquefaction plant has been added in Belgium as well as in Algeria with a CAPEX of 55.8 M€/kt/h, a FOM of 2.79 M€/year, and a lifetime of 30 years. This plant requires 0.014 GWh of electricity to process a kiloton (kt) of CO_2. A CO_2 regasification plant has been established in Algeria with a CAPEX, FOM, and lifetime of 25.1 M€/kt, 1.25 M€/year, and 30 years, respectively. Storage of liquefied CO_2 has been done with the same assumptions as in Berger et al. (2021).

Belgium is modeled with an electricity and gas demand as depicted in Fig. 2, with various means of production, including wind power, solar power, and a Combined Cycle Gas Turbine (CCGT). The solar potential is limited to 40 GW. The wind potential equals 8.4 GW and 8 GW for onshore and offshore capacities, respectively. The techno-economic parameters of each technology deployed in Belgium follow those in Berger et al. (2020).

We have also added a CO_2 source that is equivalent to 40 Mt CO_2/year, which corresponds to the energy sectors and industrial processes greenhouse gases in Belgium in 2019 (European Commission and Directorate-General for Energy, 2021, Table 4.1.1 (pp. 165-166)). We assume that we can install post-carbon capture technologies (PCCC) in these sectors.

In terms of carbon capture technologies, the model has access to direct air capture installed at the RREH, as well as a PCCC in Belgium on the 40 Mt of CO_2 per year and a PCCC installation on the CCGT.

As stated in Berger et al. (2020), the cost of PCCC is 3150 M€/kt/h of CAPEX. The variable operating and maintenance costs (VOM and FOM) have been neglected in this analysis. However, a demand of $0.4125\ GWh_{el}/kt_{CO2}$ of electricity is required. The expected lifetime is assumed to be 20 years.

Similarly, according to Berger et al. (2021), the cost of DAC is equal to 4801.4 M€/kt/h of CAPEX. Similar to PCCC, VOM and FOM are ignored. The operational requirements for DAC are $0.1091\ GWh_{el}/kt_{CO2}$ of electricity, $0.0438\ kt_{H2}/kt_{CO2}$ of di-hydrogen, and $5.0\ kt_{H20}/kt_{CO2}$ of water. The expected lifetime is assumed to be 30 years.

5.3. Scenarios explored

In this subsection, we explore several scenarios. We describe the variables that are used to differentiate the scenarios

1. Cost or Cap on CO_2: either a cap is set of 0 t/year or a price at 80 €/t or 0 €/t
2. Cost of energy not served (ENS): either ENS is not allowed or a penalty of 3000 €/MWh is imposed for each unit of unproduced energy.
3. Forcing or not the use of a given RREH.

Table 2
Parameters and objective for a 2 years optimization horizon for each scenario.

Scenario	Cap on CO_2 (kt)	Cost of CO_2 (€/t)	ENS	Cost ENS (k€/MWh)	Objective (M€)
1	0.0	0	No	–	80 004.82
2	0.0	0	Yes	3.0	77 990.20
3	No	80	Yes	3.0	75 437.39
4	No	0	Yes	3.0	72 511.43
5	0.0	0	No	–	109 441.54

The results are generated with 5 scenarios:

Scenario 1: This scenario seeks to avoid energy scarcity, whatever the cost. Therefore, no ENS is allowed. In addition, a hard constraint is set on CO_2 emissions: a cap on CO_2 is set.

Scenario 2: This scenario follows the same assumptions as scenario 1 except that it does not consider the constraint on ENS. The cost associated with electricity not served equals 3000 €/MWh, which is a standard value in the electricity context (Schröder and Kuckshinrichs, 2015).

Scenario 3: This scenario leverages the constraint on CO_2 emissions, and does not force the avoidance of ENS but is penalized by 3000 €/MWh not served. A penalty is associated with any CO_2 emission in the atmosphere in the form of a fee equal to 80 €/t - a value that reflects the current price of CO_2 in the EU-ETS trading system (Trading Economics, 2023).

Scenario 4: This scenario follows the same assumptions as scenario 3, with the difference that the cost of CO_2 is equal to 0 €/t. The aim is to showcase the system's configuration without any considerations for CO_2 emissions.

Scenario 5: This scenario follows the same assumptions as scenario 1, with the difference that the only available RREH is in Greenland.

These scenarios summarized in Table 2 vary in their degree of constraint. Scenario 1 is the most restrictive, with a cap on CO_2 emissions and no allowance for ENS. Scenario 2 allows for ENS, while scenarios 3 and 4 remove the cap and replace it with CO_2 prices of 80 € and 0 €

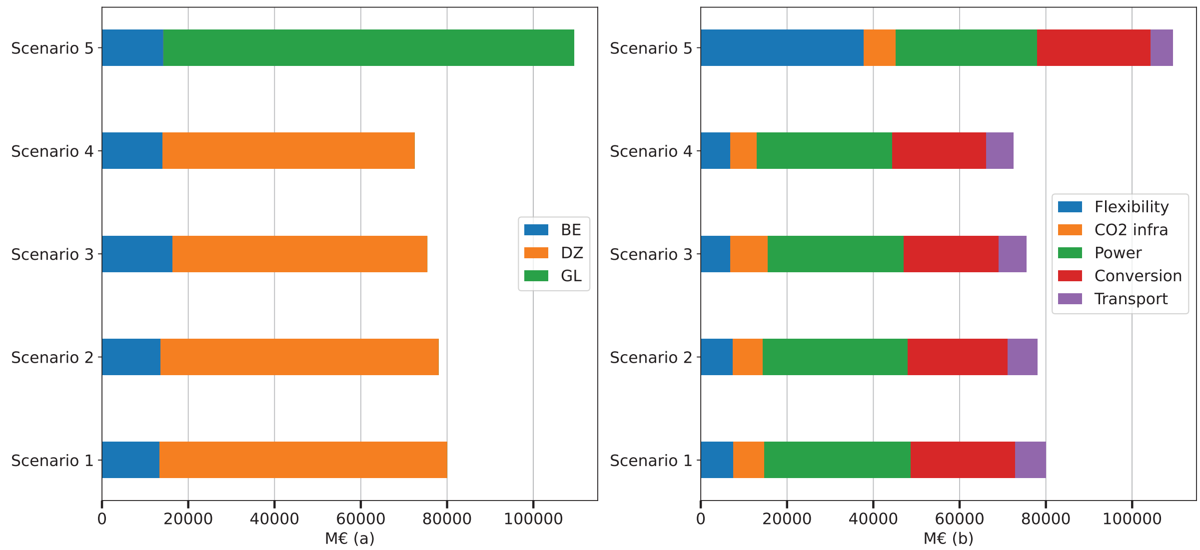

Fig. 3. (a): Breakdown of costs per scenario and per cluster (Belgium (BE), Algeria (DZ), and Greenland (GL)). (b): Breakdown of costs per scenario per asset function. Flexibility covers storage capacities, CO_2 infra covers CO_2 capture, storage, and transport, power covers means of electricity production, conversion covers all assets that convert one commodity into another and transport HVDC lines and CH4 carriers. The higher cost of scenario 5 can be attributed to the over-dimensioning of flexibility assets, particularly the storage capacities, as illustrated in Fig. 3 (b). This originates from the fact that electricity is generated solely through wind in Greenland, whereas both solar and wind electricity are generated in Algeria.

per ton, respectively. Finally, scenario 5 requires the use of the RREH in Greenland, with parameters identical to those of scenario 1.

6. Results and discussion

In this section, we present and discuss the obtained results. We opt for a cross-scenario analysis, utilizing key indicators and statistics extracted from our model, which we juxtapose with the findings of Berger et al. (2021). This comparison is meaningful due to the shared assumptions between their work and ours, with the exception of the original CO_2 installations introduced in our study. We scrutinize various aspects, including the total system cost, sizes of power and CO_2 installations, CO_2 and CH_4 costs, and the ENS. Additionally, we assess and deliberate upon the influence of uncertainty regarding the parameters of the CO_2 installations. Finally, we compare our findings with those of recent related studies.

6.1. Total cost

The results indicate that the costs associated with enabling the hub in Algeria are substantially lower than those in Greenland, as depicted in Fig. 3(a) where nothing is built in the Greenland hub from scenarios 1 to 4, despite it being available for use. This disparity in costs can be attributed to the over-dimensioning of flexibility assets, particularly the storage capacities, as illustrated in Fig. 3(b). This is primarily applicable to electricity generated solely through wind in Greenland, whereas both solar and wind electricity are generated in Algeria. This implies that the flexibility assets have to play a leading role in maintaining the minimum required electricity delivery in the electrolysis power plant.

Furthermore, a reduction in total costs is observed in the first four scenarios with respect to the objective. This is explained with the order of the scenarios based on their degree of constraint, with scenario 1 being the most constrained and scenario 4 being the least.

6.2. Power installation capacities

All power capacities installations are displayed in Table 3.

The potential in Belgium for solar energy is never reached, while for both wind offshore and onshore, the potential is reached in all scenarios.

From scenario 1 to scenario 2, the only difference being the allowance of ENS, there is an increase in the installation of controllable energy production assets. Indeed, there is a shift in capacity from CCGT to solar energy in Belgium between the first scenario and the second.

Regarding scenarios 1 and 5 – similar except for the extent of Greenland's usage in scenario 5 – solar energy in Belgium is less developed in scenario 1 than in scenario 5. This emphasizes the system trade-off between importing more or less methane from the RREH when it is cheaper. Importing from Greenland is more expensive and leads to an increase in power capacity installation in Belgium for solar, but it does not reach its maximum potential.

Another comparison can be made with the work of Berger et al. (2021), where the capacity installation in the hub for the reference scenario is 4.3 GW of solar and 4.4 GW of wind. In our case, the reference scenario 1 displays 98.16 GW and 95.21 GW, respectively. The power installation capacity is multiplied by approximately 22 while providing, on average, 282 TWh/year of gas (HHV) to serve the gas demand and part of the electricity demand in Belgium, which is 28.2 times the gas production in the original paper. Therefore, thanks to import of CO2 power requirements within the hub are less important.

6.3. CO_2 installations (transport, capture)

In Table 4, the capacities of the CO_2 capture units and the installations of transport capacity per scenario are displayed. Each time PCCC is activated, we recall that capturing CO_2 is the only means to create gas in our system, and thus a minimum installation is required to support the demand. On the other hand, the DAC is only activated when a CO_2 cap is set (scenario 1, 2 and 5). PCCC has an efficiency of CO_2 capture set to 90%, which means that a direct air capture technology asset is necessary to recover the remaining 10% of emissions in the atmosphere. This leads to a direct consequence, which is that when the DAC is available, the capacity of transport decreases because CO_2 is locally available in the hub. However, the cost of CO_2 capture by PCCC added to transport, liquefaction/regasification of CO_2 is cheaper than the cost of DAC in the RREH. The only way to put PCCC out of business would be to have a distance between the hub and the energy demand center so long that the transport cost would increase too much.

Table 3
Total power installation in GW per scenario.

Scenario	Wind onshore BE	Wind offshore BE	Solar BE	CCGT BE	Wind GL	Wind DZ	Solar DZ
1	8.40	8.00	13.42	19.58	0.00	98.16	95.21
2	8.40	8.00	17.43	15.72	0.00	94.67	91.85
3	8.40	8.00	16.77	15.86	0.00	87.69	84.90
4	8.40	8.00	17.23	15.57	0.00	86.81	84.05
5	8.40	8.00	16.90	19.58	126.48	0.00	0.00

Table 4
Capacity, in kt/h, of CO_2 capture technology and transport by hub and per scenario.

Scenario	PCCC	PCCC CCGT	DAC DZ	DAC GL	Carrier DZ	Carrier GL
1	4.11	2.34	1.40	0.00	7.443	0.000
2	4.11	2.00	1.64	0.00	6.552	0.000
3	4.11	1.83	0.00	0.00	9.359	0.000
4	5.00	1.62	0.00	0.00	9.255	0.000
5	4.11	2.98	0.00	1.14	0.000	7.905

6.4. Cost of CO_2 derived and cap of CO_2

From the first, second, and fifth scenarios, we are able to derive shadow prices thanks to the CO_2 cap constraint. These correspond to approximately 177 €/tCO2 for the first and second scenarios and 258 €/tCO2 for the fifth scenario. This shows that given the system considered, i.e., Belgium and RREH, putting a price of CO_2 equal to 177 € would avoid these emissions in the atmosphere and activate the export of CO_2 to Norway for storage purposes. In scenario 3, where a price of 80 €/tCO2 is set, there is no export of CO_2 to Norway. Therefore, a net balance of CO_2 in the atmosphere of approximately 17 Mt/year is observed. In scenario 4, where no price is fixed, similar to scenario 3 there is no export of CO_2 to Norway, and there is a net balance of CO_2 in the atmosphere which is equivalent to 24.5 Mt/year.

We would like to emphasize that the CO_2 cap in our model only considers the emissions from the industrial and energy sectors, which are fully modeled. It does not account for a part of the emissions resulting from the gas demand served. Of this demand, 32% is attributed to industrial needs, which are included in the statistics of the 40 Mt of CO_2 emitted per year (see Section 5.2), while the remaining 68% is due to heating and is not covered by our cap. This heating gas demand translates to approximately 12.3 Mt of CO_2 emitted per year.

6.5. Cost of CH4 derived

To estimate the cost of CH4 production, we first subtract from the optimal objective function the cost of the means of electricity production in Belgium (PV, on/offshore wind, CCGT), the cost of unserved energy (when applicable), and the cost related to the export of CO_2 for sequestration. All of these costs are subtracted because they do not refer directly to the cost of producing synthetic methane but rather for meeting the electricity demand in the Belgium cluster (cfr Fig. 1). Then, we divide the obtained cost by the total energy content (HHV) in CH4 produced at the output of the regasification power plant in Belgium.

These methane costs, listed in Table 5, are compared to the price of 147.9 €/MWh of methane (HHV) obtained by Berger et al. (2021). Indeed, the same methodology and assumptions have been taken in order to be able to compare the results. Our scenarios achieve a lower cost for gas production (except for Greenland). This demonstrates that PCCC, which uses smoke with a high concentration of CO_2 combined with transport, is more cost-effective than having only access to a DAC unit, as previously mentioned.

In our system, no fossil gas is available for import to Belgium; only synthetic gas produced from CO_2 capture is used. If fossil gas were still available for import, our model would seek to minimize costs and import as much cheap gas as possible while staying within our carbon budget.

Table 5
Estimation of methane price by retrieving the costs of power installations in Belgium, costs of unserved energy, and costs of exporting CO_2 for storage purposes.

Scenario	1	2	3	4	5
[€/MWh]	134.86	136.67	132.92	128.14	187.94

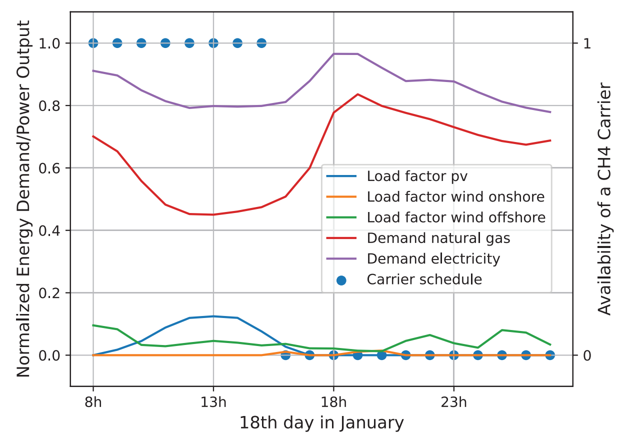

Fig. 4. The evening of January 18th led to the maximum shadow price associated with the hard constraint on ENS in scenarios 1 and 5 due to the lack of available renewable energy and high energy demand.

6.6. ENS cost discussion

The cost of unserved energy is a fixed parameter in scenarios 2, 3, and 4, but not in scenarios 1 and 5. Instead, a hard constraint is imposed to ensure that electricity demand is always met, resulting in a shadow price associated with the constraint. The maximum shadow price values for scenarios 1 and 5 are 736,139 €/MWh and 1,040,501 €/MWh, respectively. The significantly higher costs of ENS, in comparison with the 3000 €/MWh (usually used in the literature Schröder and Kuckshinrichs, 2015) set for scenarios 2, 3, and 4, are attributed to the peak in electricity and gas demand observed on January 18th at 18:00 (as shown in Fig. 4), where renewable energy load factors were low. Thus, all energy demand had to be supplied by the CCGT and gas resources.

6.7. Impact of uncertainty in CO_2-related technologies on costs

In this analysis, we replaced the deterministic values for the CAPEX of CO_2-related processes with uniform distributions, as outlined in Table 1. These distributions are then propagated through the multi-energy system optimization model using PCE (Section 4.2) to determine the statistical moments and global sensitivity indices on the total cost, shadow price and cost of methane.

The distribution of the total cost in scenario 1 is characterized by a mean of 79 989 M€ and a standard deviation of 699 M€, resulting in a Coefficient of Variation (CoV), ratio between the standard deviation and the mean, of 0.9%. Notably, the mean cost is marginally lower than the deterministic response of 80 004 M€. Consequently, there exists a 51% likelihood of realizing a total cost that is equal to or

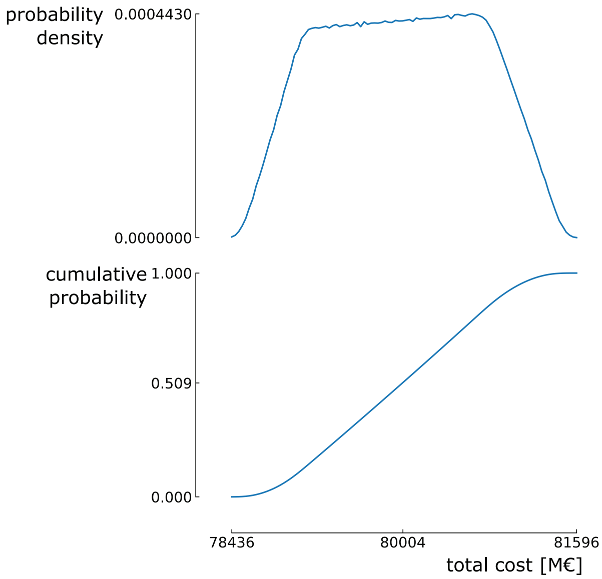

Fig. 5. The probability density function (top) and cumulative distribution function (bottom) of the total cost for scenario 1.

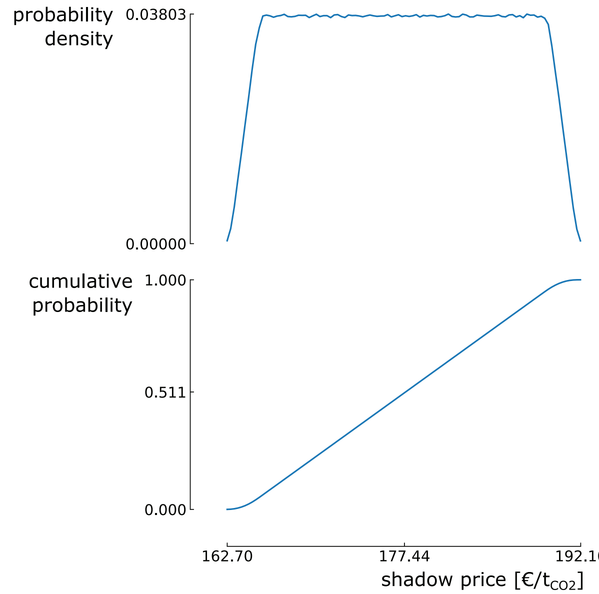

Fig. 6. The probability density function (top) and cumulative distribution function (bottom) of the shadow price for scenario 1.

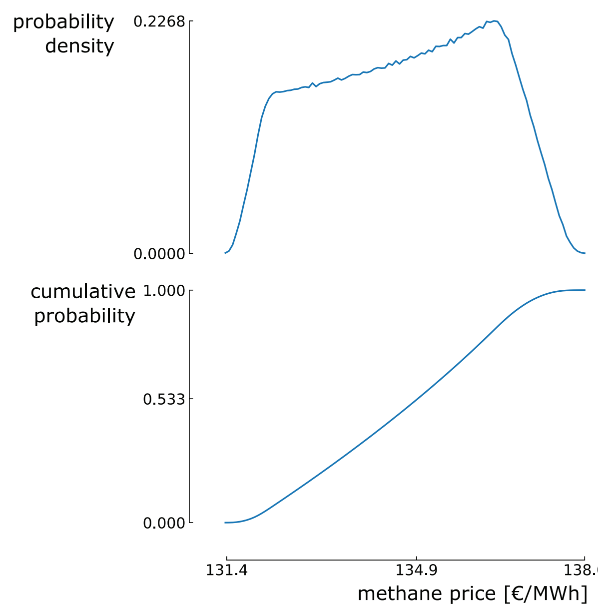

Fig. 7. The probability density function (top) and cumulative distribution function (bottom) of the methane price for scenario 1.

less than this value in practice. It is worth highlighting that this uncertainty in total cost is primarily driven by the probabilistic CAPEX related to the PCCC, as indicated by a global sensitivity index of 0.92 related to this parameter. Additionally, there is a marginal influence from the probabilistic CAPEX associated with the DAC, with a global sensitivity index of 0.07. Therefore, while the overall variance in total cost remains modest, focusing on the bulk manufacturing of PCCC units emerges as the most effective strategy for uncertainty mitigation (see Fig. 5).

The shadow price in scenario 1 follows a distribution characterized by a mean of 177.38 €/tCO2 and a standard deviation of 7.69 €/tCO2, resulting in a CoV of 4.3%. Another observation is that this uncertainty is almost entirely attributable to the distribution of the CAPEX of the DAC, as evidenced by a global sensitivity index of 0.99. The mean value of 177.38 €/tCO2 is marginally lower than the deterministic model response of 177.44 €/tCO2, resulting in a 51% likelihood of observing a value lower than the deterministic response (Fig. 6).

Consistent with the distributions on total cost and shadow price, the variance on the cost of methane is relatively limited: A standard deviation of 1.55 €/MWh and a CoV of 1.2% when measured against a mean of 134.68 €/MWh (Fig. 7, top). This variance is predominantly driven by the distribution of the CAPEX of the PCCC, as indicated by a substantial global sensitivity index of 0.97. The non-linear response of the energy system optimization model to the range of CAPEX for the PCCC results in a mean methane price below the deterministic value of 134.86 €/MWh. As a result, there is a 53% likelihood of attaining a methane price equal to or below this deterministic value (Fig. 7, bottom).

6.8. Comparison with other studies

To further compare our results, Hampp et al. (2023) found a cost estimate of 78.38 €/MWh for shipping liquid CH4 from Morocco to Germany in 2050 with a WACC of 10%. However, some discrepancies between their methodology and ours should be mentioned: (i) they did not model the energy infrastructure within the country as we did with the HVDC line, (ii) they did not consider the regasification units in the import country, (iii) they only considered one source of CO_2 from DAC, and (iv) we used a WACC of 7% instead of 10% as they did. Pfennig et al. (2023) analyzed the cost of different power-to-X fuels, notably CH4. They obtained estimates worldwide ranging from 90 to 150 €/MWh of gas considering the same electrolysis technology as us, namely PEM. They obtained an estimate of more than 120 €/MWh (LHV) for exporting this gas to Germany. The main discrepancies are (i) they did not consider PCCC to source their CO_2, and (ii) they used a WACC of 8%. It is difficult to compare results from other studies due to the numerous assumptions made, such as costs, technologies, perimeters of the model and WACC. This is the reason why we concentrate our comparison on the cost analysis presented in Berger et al. (2021), as we adopted identical technical parameters for the shared units in both systems. However, we can observe that the costs of CH_4 derived from Berger et al. (2021), Pfennig et al. (2023) and Hampp et al. (2023) are in the same order of magnitude as our reference scenario.

6.9. Relevance for practical implementation

Some companies are exploring the implementation of CO_2 loops (Tree Energy Solution, 2024). Therefore, assessing the relevance of PCCC versus DAC in their business plans is crucial. Generally, capturing CO_2 where it is most abundant is more feasible. Hence, economically, it makes sense to capture CO_2 where CO_2-intensive industries are concentrated. Moreover, this research emphasizes Algeria's competitiveness compared to Greenland as a future hub for Northern Europe.

7. Conclusion

In this study, we introduced a framework for CO_2 valorization in multiple RREH, applied to a case study focusing on Belgium as the energy demand center, along with two RREH in Greenland and Algeria, with the aim of decarbonizing the energy and industry sectors. We modeled and optimized the entire supply chain, obtaining a gas price of €135/MWh (HHV) in our reference scenario. This contrasts with the €150/MWh (HHV) reported in Berger et al. (2021), where only direct air capture was considered in the RREH for feeding CO_2 into the methanation process. Our uncertainty quantification method for the capex price of CO_2 installations (transport, capture and storage) indicates that PCCC (*i.e.* capture) contributes the most to the uncertainty. We derive a CO_2 cost of 177 € per ton to achieve emission reduction in the industrial and energy sectors in Belgium. Comparatively, the Greenland hub is less competitive than Algeria, with a methane cost of 188 €/MWh. The cost efficiency of PCCC installations in emitting countries supports the notion of investing in CO_2 infrastructure and establishing a circular CO_2 economy between energy demand centers and RREH as we proposed.

Glossary

BE	Belgium
CAPEX	Capital Expenditure
CCGT	Combined Cycle Gas Turbine
DAC	Direct Air Capture
DZ	Algeria
EDC	Energy Demand Center
ENS	Energy Not Served
ETS	Emission Trading System
GBOML	Graph Based Optimization Modeling Language
GL	Greenland
HHV	Higher Heating Value
LHV	Lower Heating Value
OPEX	Operational Expenditure
PCCC	Post Combustion Carbon Capture
PV	Photovoltaic
RREH	Remote Renewable Energy Hub

Nomenclature

Sets and indices

$\mathcal{E}, e$ set of hyperedges and hyperedge index

$\mathcal{G}$ hypergraph with node set $\mathcal{N}$ and hyperedge set $\mathcal{E}$

$\mathcal{I}^n, i$ set of external variables at node n, and variable index

$\mathcal{N}, n$ set of nodes and node index

$\mathcal{T}, t$ set of time periods and time index

Parameters

$v \in \mathbb{N}$ number of years spanned by optimization horizon

$\kappa_i \in \mathbb{R}_+$ maximum flow capacity of commodity i

$\zeta^n \in \mathbb{R}_+$ annualized CAPEX of node n (flow component)

Variables

$q^n_{it} \in \mathbb{R}_+$ flow variable i of node n at time t

CRediT authorship contribution statement

Dachet Victor: Writing – original draft, Visualization, Software, Methodology, Data curation, Conceptualization. **Benzerga Amina:** Visualization, Conceptualization, Methodology . **Coppitters Diederik:** Writing, Software, Methodology. **Contino Francesco:** Reviewing. **Fonteneau Raphaël:** Writing – original draft, Methodology, Conceptualization. **Ernst Damien:** Reviewing, Funding Acquisition.

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

A link with the software and data is available in the manuscript.

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