Highlights

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

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- We demonstrate PCCC technology potential for reducing RREH's CH4 production cost;
- We derive a carbon price threshold for crucial industrial decarbonization;
- An uncertainty analysis has been carried out on the reference scenario.

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

Dachet Victor[a,*], Benzerga Amina[a], Coppitters Diederik[b], Contino Francesco[b], Fonteneau Raphaël[a] and Ernst Damien[a,c]

[a] University of Liège, Pl. du Vingt Août 7, Liège, 4000, Liège, Belgium
[b] Institute of Mechanics, Materials and Civil Engineering (iMMC), Université catholique de Louvain (UCLouvain), Place du Levant, 2, Ottignies-Louvain-la-Neuve, 1348, Brabant Wallon, Belgium
[c] Telecom Paris, Institut Polytechnique de Paris, 19 place Marguerite Perey, Paris, 91123, Palaiseau, France

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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 (RE). Such renewable energy is generated in RREHs, 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 RREHs, 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. For example, this price threshold may give relevant information for calibrating the EU Emission Trading System so as to trigger the emergence of the multi-RREH.

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 Utilisation), 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.

As in our previous work [12] from which this paper is an extended version, we build on top of the Remote Renewable Energy Hub (RREH) approach [3] 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, 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.

We propose a methodology for assessing the technico-economic feasibility of exporting CO_2 into RREH where synthetic CO_2-neutral methane would be generated using locally produced green H2. We formalise an optimisation 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 modelling of Belgium's energy system, including gas and electricity demand, and main CO_2 emitters. We rely on previously published approaches to develop our approach [3], and, in particular, we use the GBOML language [25] to model the energy system and to optimize 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) [10].

Several methods exist to characterize parametric uncertainties in the context of energy systems [24], including,

*Corresponding author
victor.dachet@uliege.be (D. Victor)
ORCID(s): 0009-0005-6945-1111 (D. Victor)

among others, interval analysis, fuzzy set theory and Probability Density Functions (PDFs) [14]. 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 [29].

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 [13], support vector machines [7], Analysis Of Variance (ANOVA) [21]) 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 [32] 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.

In summary, our methodology is also evaluated in the Belgian context: we consider Belgian CO_2 emissions and Belgian gas and electricity demand. CO_2 may be captured using Post Combustion Carbon Capture (PCCC) in Belgium or DAC in RREH locations. CO_2 neutral synthetic methane will be produced in a remote energy hub from where it would be shipped back to serve the Belgian gas demand. We derive a CO_2 emission cost in order to have a neutral emission system. We also determine a value of lost load (*i.e.* a price associated with a lack of energy service) in order to serve the energy demand at all times. Several scenarios are studied with different prices of CO_2 emissions, allocation or not of unserved energy and forcing of a given RREH. Additionally, an uncertainty quantification analysis is conducted on the CO_2 infrastructure CAPEX in the first scenario.

2. Related Work

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 [8], [37], sometimes referred to as Global Energy Interconnection approaches [23], 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 centres. 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 [34] 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 [31]. Resource and demand configurations combining several types of resources as well as demand time zones show better results [37].

Multi-energy systems approaches [28, 30] 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 [22], offer a CO_2 neutral solution to serve gas demand, but also a way to store vast quantities of energy issues from renewable sources [5]. Recently, Berger et al. have proposed a modelling framework [3] for assessing the techno-economics viability of carbon-neutral 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 Berger et al. [20, 26, 33], however, the contribution of Berger et al. is the introduction of remote energy production, far from the demand. Our contribution is in line with the latter.

As this work aims to enhance the value of CO_2, it is closely linked to various policy mechanisms that establish a price on CO_2 emissions, such as a carbon tax or a carbon market 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.

3. CO_2 Valorisation in a Multi-Remote Renewable Energy Hubs Approach

The Remote Renewable Energy Hub concept was first introduced in [3], 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 [8] and multi-energy systems approaches. These approaches aim at optimising the generation and utilisation 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 [3], 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

[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_enand in [6].

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 RREHs, 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.

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 RREHs: 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 Figure 1.

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

4. Modelling

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 [25], 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 RREHs and the energy demand center in our context.

The formalism utilized in this study follows the framework introduced in [3]. 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 $\mathcal{T} = \{1, \ldots, T\}$.

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:

- Centralised 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 optimisation horizon, i.e., $\forall t \in \{1, \ldots, T\}$.
- 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 optimisation period, i.e., $\forall t \in \{1, \ldots, T\}$.
- Linear modelling of technologies: All technologies and their interactions are modelled 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 modelled in this approach. This can be viewed as an extension of the copper plate modelling 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 [2], [3]. Additionally, the local objective function corresponding to the CAPEX is modelled 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,

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

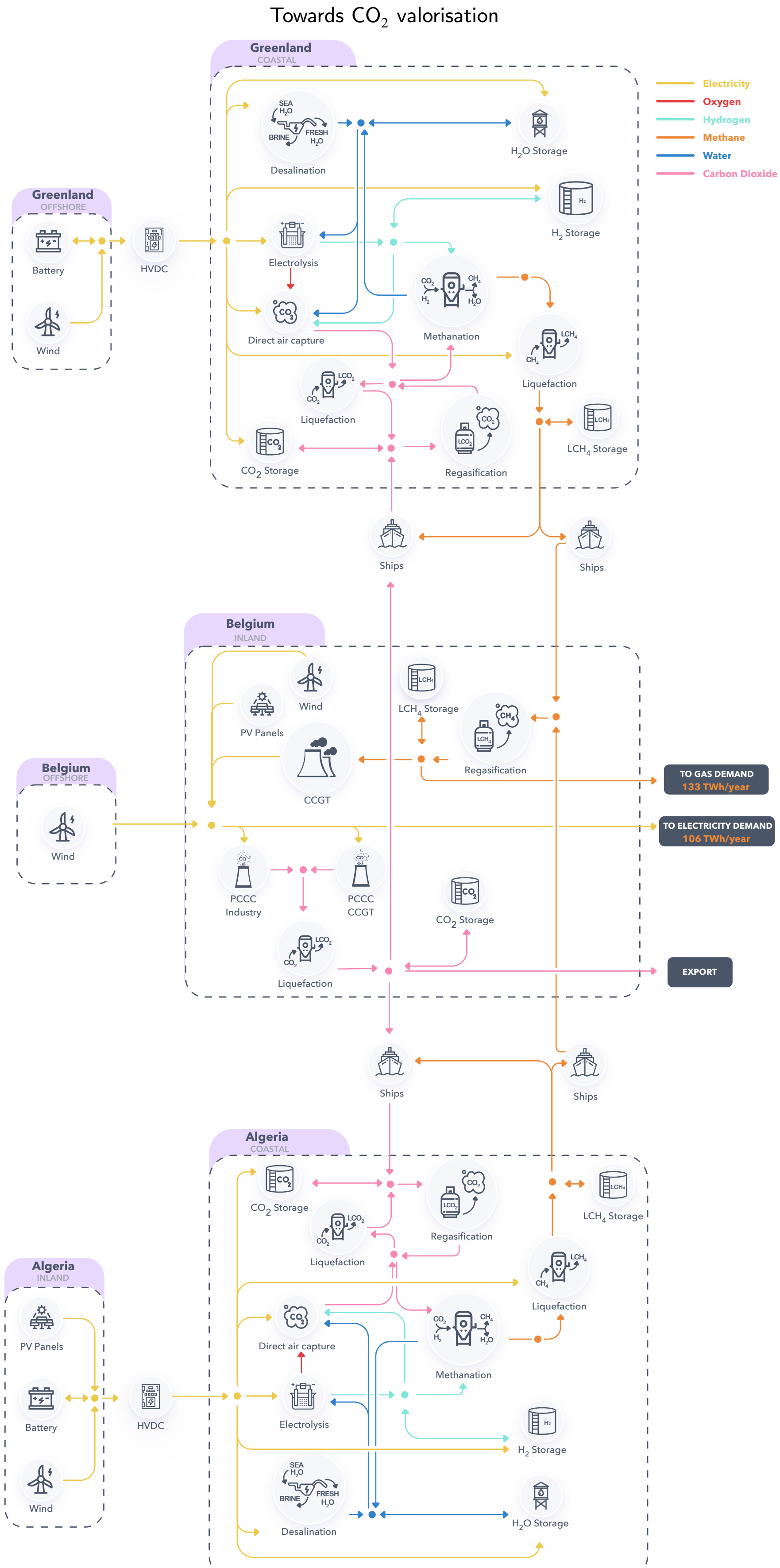

Figure 1: A schematic illustration of the remote energy hub. CO_2 being captured, it may be used to synthesize fuel either locally either in a remote energy hub where renewable energy may be cheaper and more abundant.

the annual cost $zeta^n$ of investing in technology n writes:

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

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

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

with $\mathcal{A}$ and $\mathcal{C}$ 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 Equation 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 [4, Chapter 4].

4.2. Uncertainty quantification

The optimization problem outlined in subsection 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 [10]. The optimization problem $\mathcal{M}$ depending on such random parameters can be defined as a function:

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

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:

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

where $P_{\boldsymbol{X}}$ 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 $\text{Var}[Y]$ to each input parameter X_i. To do so, the Sobol' indices are adopted, corresponding to:

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

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

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. To facilitate this approach, we utilized the open-source Python framework Rheia [11]. We refer to Sudret et al. [36] 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 et al. [36], 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% [36]. 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 analyse 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 cover two years: 2015 and 2016 at an hourly resolution. It is used to characterize energy demand as well as load factors for renewable energy sources. The data have been retrieved from different sources [2], [3]. 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 [17]. The profiles for the RREH located in Algeria are extracted with the same methodology as in [3]. For the RREH situated in Greenland, the profiles of renewable energy are extracted thanks to the MAR model [18] and given a power curve for an offshore wind turbine MHI Vestas Offshore V164-9.5MW.

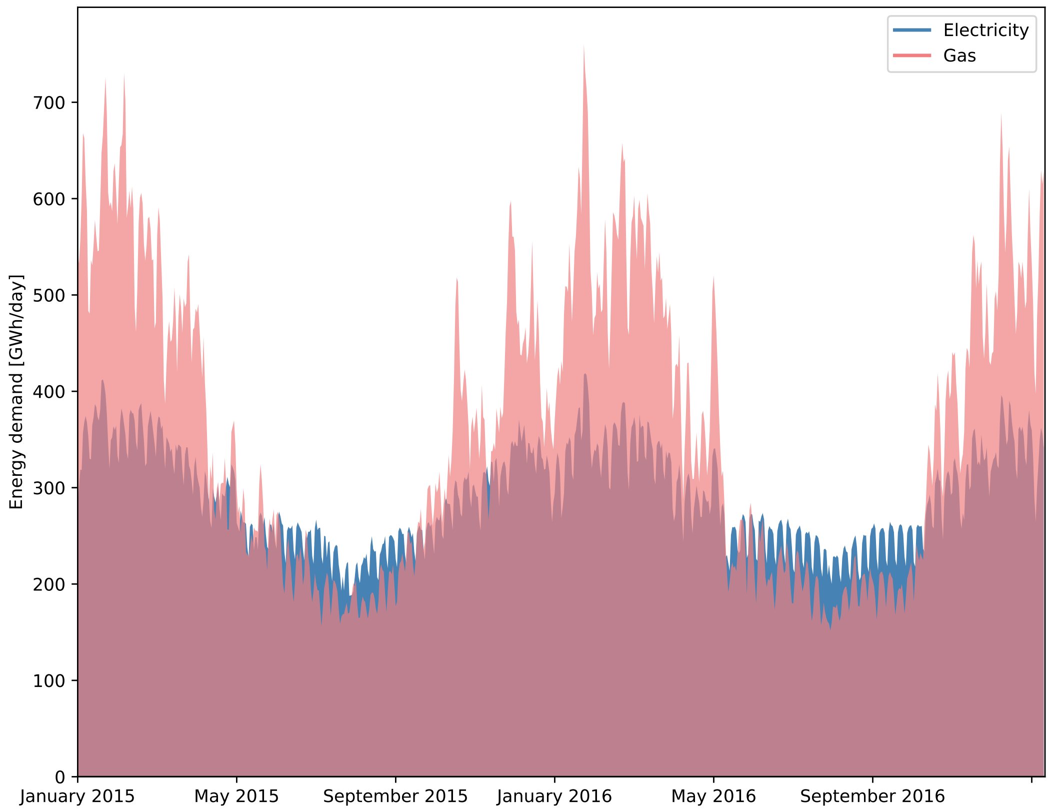

Figure 2: Daily aggregated profiles of electricity and natural gas demand covering the years 2015 and 2016 spanned by the optimisation.

Energy consumption

The energy consumption data is collected for two energy vectors: gas ([19]) and electricity ([16]) with the same methodology as in [2]. In Figure 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 [2, 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 [24]. 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 ($\pm$30%) and narrower variations for mature technologies ($\pm$10%), following the approach proposed by Moret et al. [27]. The specific uncertain parameters are detailed in Table 1.

5.2. Model Configuration

Our model consists of three main components (see Figure 1): the energy demand centre located in Belgium and two Remote Renewable Energy Hubs (RREHs) situated in Algeria and Greenland. The RREH in Algeria is modelled as described in [3] 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 modelled, with the exception of the

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

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.

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 5M€/kt, a lifespan of 40 years, and an average daily energy consumption of 0.0150 GWh/day. CO_2 transport data was obtained from [1]. The loading and traveling time for these boats are assumed identical to those for liquefied methane carriers [3], *i.e.* 24 and 116 hours, 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.

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 [3].

Belgium is modelled with an electricity and gas demand as depicted in Figure 2, with various means of production, including wind power, solar power, and a combined cycle gas turbine. The solar potential is limited to 40GW. 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 [2].

We have also added a CO_2 source that is equivalent to 40Mt CO_2/year, which corresponds to the energy sectors and industrial processes greenhouse gases in Belgium in 2019 [9, 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 RREHs, as well as a PCCC in Belgium on the 40Mt of CO_2 per year and a PCCC installation on the CCGT.

As stated in [2], the cost of PCCC is 3150M€/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 [3], 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. Results

In this section, 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 energy not served 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.

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 energy not served. The cost associated with electricity not served equals 3000€/MWh, which is a standard value in the electricity context [35].

Scenario 3: This scenario leverages the constraint on CO_2 emissions, and does not force the avoidance of energy not served 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 [15].

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 energy not served. Scenario 2 allows for energy not served, while

Scenario	Cap on CO_2 (kt)	Cost of CO_2 (€/t)	ENS	Cost ENS (k€/MWh)	Objective (M€)
1	0.0	0	No	-	80004.82
2	0.0	0	Yes	3.0	77990.20
3	No	80	Yes	3.0	75437.39
4	No	0	Yes	3.0	72511.43
5	0.0	0	No	-	109441.54

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

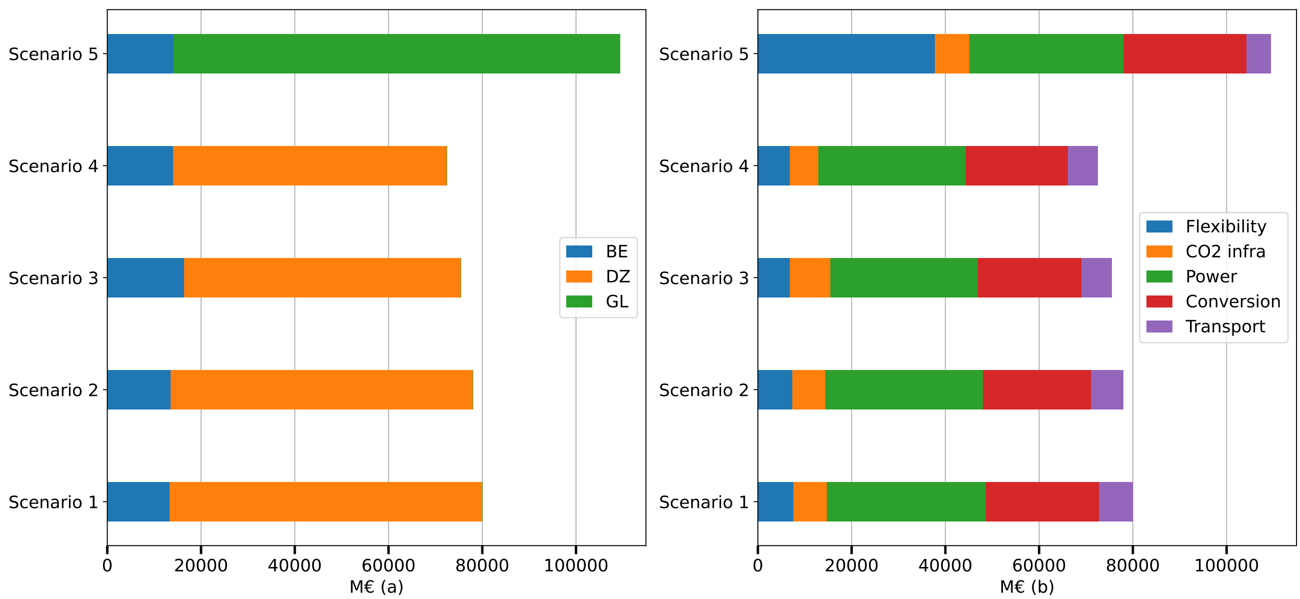

Figure 3: (a): Breakdown of costs per scenario and per cluster (Belgium (BE), Algeria (DZ), and Greenland (GL)). (b): Breakdown of costs per scenario per asset function. Flexibility covers storage capacities, CO_2 infra covers CO_2 capture, storage, and transport, power covers means of electricity production, conversion covers all assets that convert one commodity into another and transport HVDC lines and CH4 carriers.

scenarios 3 and 4 remove the cap and replace it with CO_2 prices of 80€ and 0€ per ton, respectively. Finally, scenario 5 requires the use of the RREH in Greenland, with parameters identical to those of scenario 1.

5.4. Analyses and Discussion

In this section, we introduce and discuss the results in detail. We choose to present a cross-scenario analysis in light of key indicators and statistics extracted from the model.

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 Figure 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 Figure 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.

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

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 3
Total Power installation in GW 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

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

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 [3], where the capacity installation in the hub for the reference scenario is 4.3GW of solar and 4.4GW of wind. In our case, the reference scenario 1 displays 98.16GW and 95.21GW, respectively. The power installation capacity is multiplied by approximately 22 while providing, on average, 282TWh/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.

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 centre so long that the transport cost would increase too much.

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 17Mt/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 24.5Mt/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 subsection 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.

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 Figure 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 [3]. 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

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

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.

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.

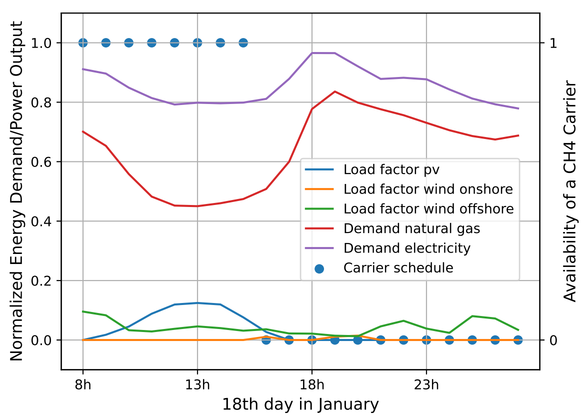

Figure 4: Evening of January 18th leading to the maximum shadow price associated with the hard constraint on energy not served in scenarios 1 and 5.

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 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 Figure 4), where renewable energy load factors were low. Thus, all energy demand had to be supplied by the Combined Cycle Gas Turbine (CCGT) and gas resources.

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 (subsection 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 79989 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 80004 M€. Consequently, there exists a 51% likelihood of realizing a total cost that is equal to or 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.

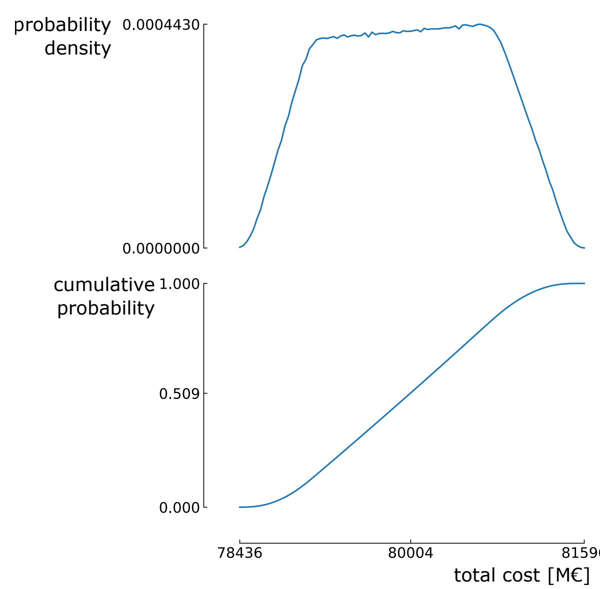

Figure 5: The probability density function (top) and cumulative distribution function (bottom) of the total cost for scenario 1.

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 (Figure 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 (Figure 7, top). This variance is predominantly driven by the distribution of the CAPEX of the PCCC, as indicated

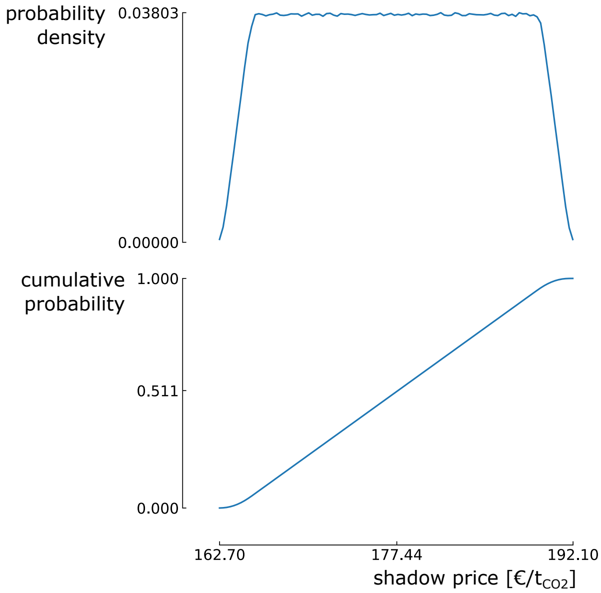

Figure 6: The probability density function (top) and cumulative distribution function (bottom) of the shadow price for scenario 1.

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 (Figure 7, bottom).

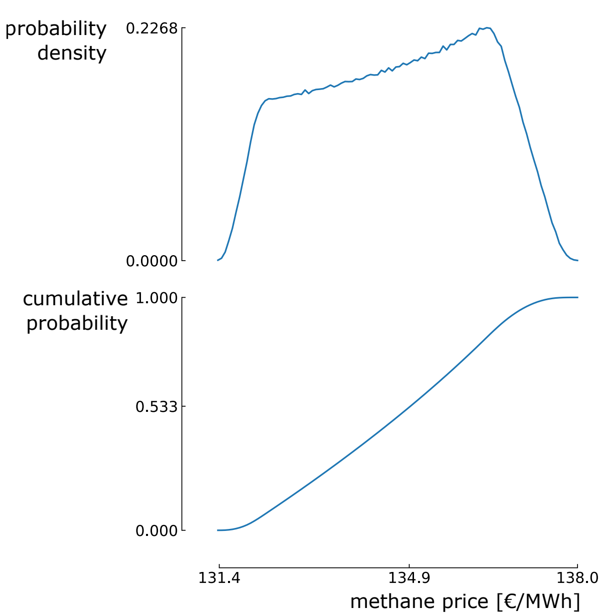

Figure 7: The probability density function (top) and cumulative distribution function (bottom) of the methane price for scenario 1.

6. Conclusion

In this work, we present our framework of multi-remote energy hubs with capture of CO_2 enabled in an energy demand center and its valorization by synthesizing methane in remote renewable energy hubs. We demonstrate the feasibility of serving the energy demand in 2050 of an entire country with only renewable energy and gas power plant fueled by synthetic methane while decarbonizing the energy and industry sectors on a case study implying Belgium as an energy demand center and two RREHs: Greenland and Algeria. Our reference scenario exhibits a gas price of 135 €/MWh instead of 150 €/MWh in [3] where only direct air capture was available in the RREH in order to feed CO_2 into the methanation process. The methane price in the reference scenario, ranging from 131 to 138 €/MWh due to the uncertain CAPEX associated with emerging and mature CO_2 processing technologies, exhibits a 53% likelihood of remaining below the deterministic reference scenario value of 135 €/MWh. This shows the potential of Post Combustion Carbon Capture installations in the context of remote renewable energy hubs supply chains. We also derive a cost of CO_2 of 177€ per ton in order to avoid any emission in the industrial and energy sector in Belgium. Finally, our model effectively captures the "competition" between different RREHs and is able to select exactly in which investments should be prioritized. In our simulations, the investments were made only for the RREH located in Algeria. In this respect, it would be interesting to study further how the different devices structuring the RREH in Greenland should be modified to become competitive with the RREH located in Algeria. This could be done, for example, by modifying the wind turbines selected for the Greenland hub so that they can operate with higher nominal wind speeds and higher cut-off speeds in order to better exploit the strong winds in this area.

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B. 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 Optimzation Modeling Language
GL	Greenland
HHV	Higher Heating Value
OPEX	Operational Expenditure
PCCC	Post Combustion Carbon Capture
PV	Photovoltaic
RE	Renewable Energy
RREH	Remote Renewable Energy Hub
RES	Renewable Energy Sources

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

$\nu \in \mathbb{N}$ number of years spanned by optimisation horizon

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

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

Variables

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

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