Impact of Uncertainties on the Design and Cost of CCS From a Waste-to-Energy Plant

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Uncertainties are an inherent and important element of novel systems with limited large-scale industrial experience and must be taken into account in order to enable the design of cost-efficient energy systems. This paper investigates the optimal design of carbon capture and storage from a waste-to-energy plant under uncertainties. With the aim of providing a better understanding of the impact of uncertainties on the design and cost of CCS chains, as well as the capture technology selection, the case of a hypothetical 40 MW waste-to-energy plant located in Norway is considered. The impact of key technical and cost uncertainties on the cost of different CO_2 capture and CCS chain options are investigated using an in-house techno-economic CCS assessment tool combined with an uncertainty quantification framework. When the different capture options are compared on a deterministic basis, the advanced amine yields the best performances (CO_2 avoidance cost of 153 €/tCO_2, avoided), followed by the membrane process based on partial capture (200 €/tCO_2, avoided) and MEA-based capture (217 €/tCO_2, avoided). However, in contrast with the advanced amine, the partial capture considered in the membrane process does not enable net negative CO_2 emissions. Once technical and cost uncertainties are taken into account, the advanced amine-based capture remains the best option, however the MEA-based capture outperform the membrane process. Finally, the stochastic optimization showed that the uncertainties considered do not impact the optimal capture capacity in this case. The full CCS chain perspective is then included through two chain options: a nearby offshore saline aquifer or an offshore CO_2 EOR storage located further away. The EOR-based chain leads to the best performances (187 vs. 202 €/tCO_2, avoided) both on a deterministic basis and when different uncertainty scenarios are considered. However, as a shared transport and storage infrastructure is considered, uncertainty regarding the amount of CO_2 coming from nearby industries leads to a different optimal design of the chain (pipeline diameter and ship capacity). Finally, uncertainties on the EOR response to CO_2 injection can significantly reduce the potential of the CO_2 EOR-based chain and lead to cases in which the saline aquifer-based chain would be optimal.

Keywords: carbon capture and storage, waste-to-energy, uncertainties, techno-economic, solvent-based CO_2 capture, membrane-based CO_2 capture, CO_2 enhanced oil recovery

INTRODUCTION

The International Energy Agency forecasts that Carbon Capture and Storage (CCS) will contribute to 14% of the reduction in anthropogenic CO_2 emissions in the 2 Degree Scenario (2DS) (IEA, 2016). CCS is a key measure to enable decarbonization of non-power related industrial emitters such as cement plants, refineries, metal production, etc. (IEAGHG, 2017, 2018; Gardarsdottir et al., 2019). In several of these cases, CO_2 is a by-product of the production process, which makes it difficult to reach the required deep decarbonization of the industrial sector without CCS. Additionally, CCS from biogenic sources, such as waste-to-energy, is foreseen as a critical pathway to limit the global warming to 1.5°C above pre-industrial levels (IPCC, 2018), as specified in the Paris Agreement.

Two of the main barriers to the implementation of CCS are the current high cost and uncertainties. The CO_2 capture section is the largest contributor to the cost of CCS, compared to the cost of transport and storage. Solvents such as monoethanol amine (MEA), considered to be the most mature CO_2 capture technology are still in the demonstration phase. Novel capture technologies (advanced solvent, membrane, low-temperature, absorption, calcium looping) that show potential for cost reduction are at a lower technology readiness level (TRL) (Boot-Handford et al., 2014). There is always some uncertainty in certain parameters when designing these separation processes—related to physical properties, performance or cost. The lower the TRL of a process the greater the uncertainty associated with its performance due to insufficient testing at the different scales required. Choosing a particular capture technology for an application without considering the uncertainties related to their respective levels of development can lead to misleading conclusions and financial risks.

The CCS value chain is a complex system consisting of one or more emission sources with CO_2 capture and conditioning at each capture location. These feed into a CO_2 transport infrastructure that includes a pipeline network and/or ships for transport leading to possibly multiple locations for CO_2 storage or EOR in saline aquifers, depleted gas or oil fields, etc. Even the simplest CCS value chain with one emission source with CO_2 capture, conditioning, pipeline transport, and storage in a saline aquifer is a complex system that may involve several operators along the chain. The uncertainties in a system increase with its complexity. Thus, considering uncertainties when designing CCS chains is critical.

Uncertainties are an inherent and important element of novel systems with limited large-scale industrial experience and must be taken into account in order to enable the design of cost-efficient energy systems (Rubin, 2012). Uncertainty is not a well-defined concept. One aspect of uncertainty is its use to identify that there is a probability that some assumptions made during design and modeling are incorrect. Another aspect is

related to external risks where the presence of entirely unknown facts that might have a bearing on the future state of the system. Uncertainties throughout the CCS value chain include technology, engineering performance, economics, policy, and market forces.

Uncertainties have typically been taken into account in many studies via simple, single-parameter sensitivity analyses to understand the impact of a given parameter on the overall cost and identify the most critical parameters. However, more complex approaches such as uncertainty quantification approaches can be used to understand the impact of underlying uncertainties on the overall costs of a CCS chain, as well as to enable better design at the chain level. These approaches present several advantages compared to sensitivity analyses. First, it enables the integration of several uncertainties simultaneously to take into account synergies and canceling effects, which cannot be taken into account through simple sensitivity analyses. For example, having strong uncertainties on both membrane properties (permeance and selectivity) and membrane cost can have a very strong impact on the performance of a membrane-based CCS chain. Secondly, such approaches provide a cost performance probability, instead of a single fixed value, which provides a stronger understanding of the performance probability of a given chain and its associated financial risk. For instance, a given CCS chain might be preferred due to low uncertainty in its cost despite being more expensive. Uncertainty quantification has been used earlier in the field of CCS to identify the effect of uncertainties of capture processes from technical and economic perspectives (Rao and Rubin, 2002; Nord et al., 2010; Hanak et al., 2016; Raksajati et al., 2018). An extensive approach to study the effect of various uncertainties, discussed above, in CCS chains has not yet been undertaken.

In this paper, we investigate the optimal design of a CCS chain from a Waste-to-Energy (WtE) plant under uncertainty. The uncertainties will be applied in a layered stepwise approach to better understand their impact on the capture, as well as a simple and a more complex CCS chain. The emphasis of this work is to provide a better understanding of the impact of uncertainties on the design of CCS chains and capture technology selection. In order to do so, the impact of key technical and cost uncertainties on the cost of different CO_2 capture and CCS chain options are investigated using an in-house techno-economic CCS assessment tool (Jakobsen et al., 2014, 2017) combined with an uncertainty quantification framework.

This paper is structured as follow. First, the case study including the CCS chain options is presented. The methodology adopted in this study is then presented. The results are split into two sections. The first looks at the WtE plant with only CO_2 capture and conditioning, while the full CCS chain perspective is considered in the second. Finally, key findings are provided in the conclusion section.

CASE STUDY

This section introduces the waste-to-energy plant considered for the analysis. The three CO_2 capture options for post-combustion capture included, and different CCS transportation and storage

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Abbreviations: 2DS, 2 Degree Scenario; BECCS, bioenergy with CCS; CAC, CO_2 avoidance cost; CCR, CO_2 capture ratio; CCS, carbon capture and storage; DAC, direct air capture; EOR, Enhanced oil recovery; LCOE, levelized cost of electricity; MEA, monoethanol amine; MSW, municipal solid waste; TRL, technology readiness level; UQ, uncertainty quantification; WtE, waste to energy.

options in the CCS chain investigated in the study are also presented.

Waste-to-Energy Plant

With the potential implementation of CCS on the Klemenstrud waste-to-energy plant as part of the Norwegian full-scale CCS project (Ministry of Petroleum and Energy, 2016), interest in retrofitting CCS on waste-to-energy has been rising in Europe, especially in Norway and Netherlands (Ministry of Petroleum and Energy, 2016; Stuen, 2019).

In the present study, a hypothetical waste-to-energy plant able to process 70 t/h of municipal solid waste (MSW) and resulting in an installed power production capacity (without CCS) of 40 MWe is considered. The MSW characteristics considered in this study (Haaf et al., under review), as well as the typical origins of MSW (Vainikka et al., 2012) are presented in **Table 1**. The plant emits a flue gas containing 10% CO_2 leading to, on average[1], 502 kt of CO_2 (biogenic and non-biogenic) released to the atmosphere every year (Haaf et al., under review). The CO_2 emissions to the atmosphere associated with this power production are thus 1.684 tCO_2/MWh, of which 65% are biogenic (Haaf et al., under review). Despite the CO_2 concentration being lower than that of non-power industrial sources like cement or steel, CCS from a WtE plant offers several advantages. First, the plant produces steam that could be used for CO_2 regeneration when using solvent-based CO_2 capture. This compared positively with other industrial CO_2 capture cases where the steam requirement is met with, for example, a natural gas boiler (Roussanaly et al., 2017). Furthermore, CCS from such a plant could be used to unlock negative emissions as nearly two-thirds of the plant emissions are biogenic in nature.

In this work, the waste-to-energy plant is assumed to be located on the coast of the Bergen area (Norway), as shown in **Figure 1**. Two storage options are considered. The first option is an offshore saline aquifer, on the Norwegian continental shelf, located about 100 km from the WtE plant. The second option is CO_2 storage associated with enhanced oil recovery (EOR) in a Norwegian reservoir located 250 km from the WtE plant. Although this storage option is located further away than the first one, the higher cost associated with transport could be offset by revenues associated with the value creation through CO_2 EOR (Roussanaly and Grimstad, 2014). The foreseen locations of both storage options are shown in **Figure 1**.

CO₂ Capture and CCS Chain Options

In order to better understand the potential of CCS from WtE plants, as well as the impact of uncertainties and fluctuations on its cost and design, five CCS "chain" options are considered. The three first focus solely on different CO_2 capture options and thus only consider CO_2 capture and conditioning from the WtE plant (i.e., CO_2 transport and storage are not included in these CCS "chains"). These three chains are henceforth referred to as capture chains rather than CCS chains. The last two chains include CO_2 capture, conditioning, transport and storage. The operations

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TABLE 1 | (A) Key characteristics of the MSW considered in this study (Haaf et al., under review) and (B) typical origins of MSW (Vainikka et al., 2012).

Molecular composition (wt%)		Source	wt% range
$C_{organic}$	18.8	Organics	30–40
C_{fossil}	10.1	Paper/cardboard	15–25
H	3.2	Textiles	1–5
N	0.5	Plastics	7–15
S	0.1	Metals	3–4
O	23.1	Glass	4–7
Cl	0.4	Other	18–30
H_2O	25		
Ash	18.8		
LHV (MJ/kg)	10		

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considered in each of the five CCS chains are illustrated in **Figure 2**.

In the first capture chain, referred as chain A, the WtE plant is retrofitted with monoethanol amine-based (MEA) post-combustion CO_2 capture. While MEA-based CO_2 capture is not the most energy efficient CO_2 capture technology option, it is one of the most mature and well-characterized CO_2 capture technologies. It thus presents limited uncertainties (Morgan et al., 2015; Kuncheekanna et al., 2019).

The second capture chain, referred as chain B, investigates the cost reduction potential which would be achieved through an advanced amine. The amine is assumed to achieve a 20% reduction in steam consumption associated with CO_2 regeneration and an overall investment cost increase of 10% (Adams et al., 2017; Roussanaly et al., 2019). Larger uncertainties compared to the MEA solvent case are expected in the advanced amine case.

The third capture chain, referred as chain C, considers the decarbonization of the WtE plant based on post-combustion CO_2 capture membranes. While membrane-based CO_2 capture from a flue gas with a CO_2 content around 10% has been shown be less competitive than solvent-based technologies at high CO_2 capture ratios, membranes with high performances have been shown to exhibit a stronger potential when partial capture is considered (Roussanaly et al., 2018). Here, an advanced membrane with a CO_2/N_2 selectivity of 75 and a CO_2 permeance of 15 m^3_{STP}/(m^2.h.bar) is considered. This membrane is based on expected material developments at NETL and is not currently available at implementation scale (Budhathoki et al., 2019).

The first full CCS chain, referred as chain D, considers CCS from the WtE plant with saline aquifer storage at the S1 location (see **Figure 2**). After an advanced amine-based capture and conditioning, the CO_2 captured from the WtE plant is combined with 1 $MtCO_2$/y coming from other nearby sources before being transported to the storage location. Based on the distance and volume involved, the most cost-efficient option to transport the CO_2 to the storage location is via pipeline (Roussanaly et al., 2014).

Meanwhile, the second full CCS chain, referred as chain E, considers CCS from the WtE plant with CO_2 EOR storage at the

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[1]Considering an average utilization rate of 85%.

S2 location (see **Figure 2**). Like chain D, the capture process is based on the advanced amine-based capture and the emissions of the WtE plant are combined before transport and storage with 1 $MtCO_2/y$ coming from other nearby sources. While CO_2 EOR enables revenues associated with the produced oil, a drawback of such storage option is that the amount of CO_2 which can be injected for storage decreases over the years[2]. To ensure that the emissions of the WtE plant and the nearby plants are handled appropriately, the excess CO_2 which cannot be stored in the oil reservoir is stored in a nearby saline aquifer located 10 km from the oil reservoir. Based on the distances and volumes considered, the most cost-efficient option to transport the CO_2 from the capture site to the oil reservoir is via ship while the transport of CO_2 from the oil reservoir to the saline aquifer is via pipeline (Roussanaly et al., 2014).

Finally, it is worth noting that unless otherwise specified, a 90% CO_2 capture ratio (CCR) of the WtE plant's emissions is sought for all five CCS chain options.

METHODOLOGY

The following section describes the methodology adopted to evaluate the cost of CCS from the WtE plant with and without uncertainties. The CCS infrastructure is modeled using the iCCS[3] tool developed by SINTEF Energy Research for integrated techno-economic modeling of CCS (Jakobsen et al., 2014, 2017). The iCCS tool is combined with an uncertainty

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[2]Over the years the reservoir produces more and more CO_2 which need to be rejected, after separation. This limits the amount of CO_2 which can be imported if the injection rate is to be constant over the project duration.

[3]iCCS stands for Integrated techno-economic and environmental modeling of CCS.
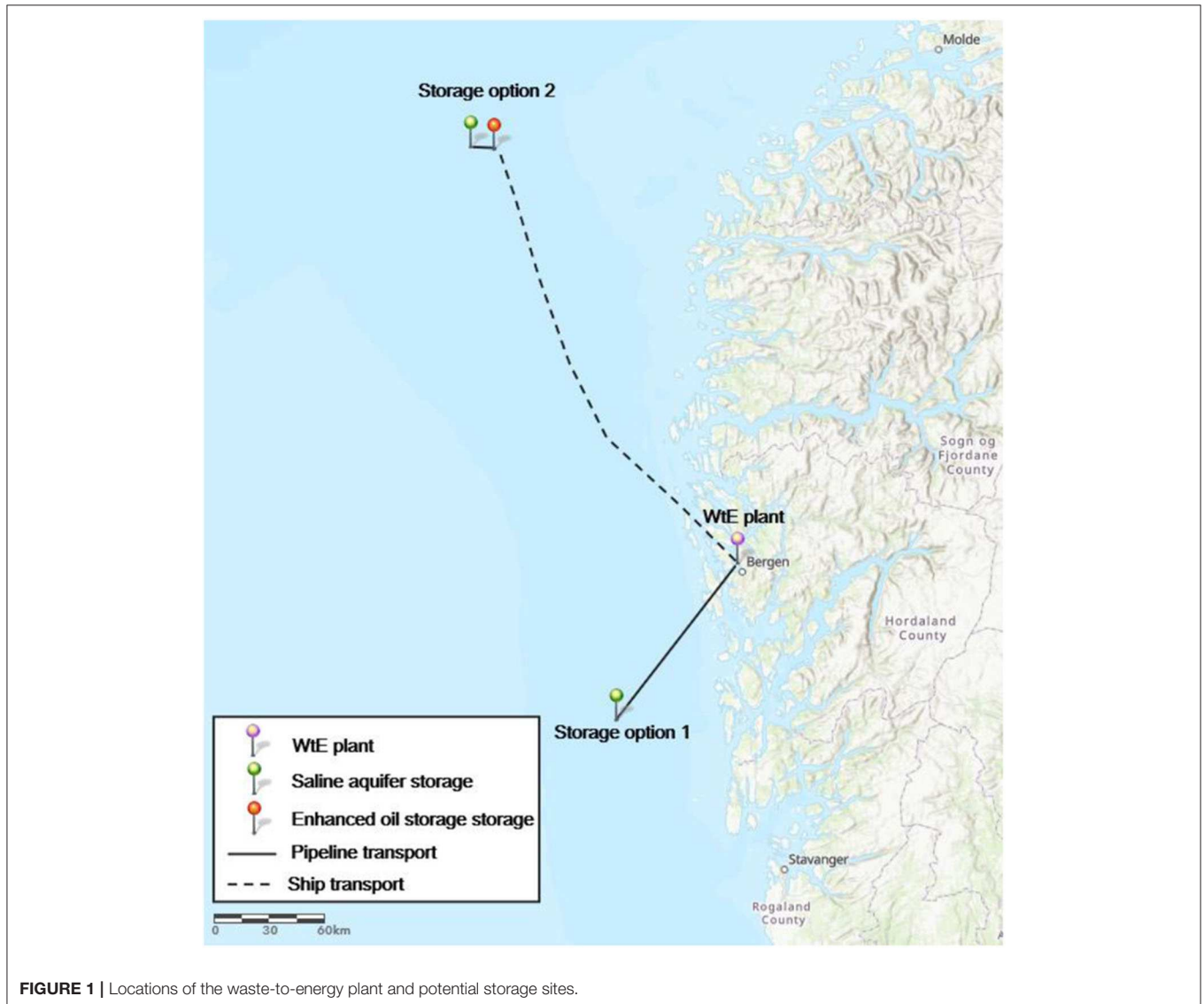
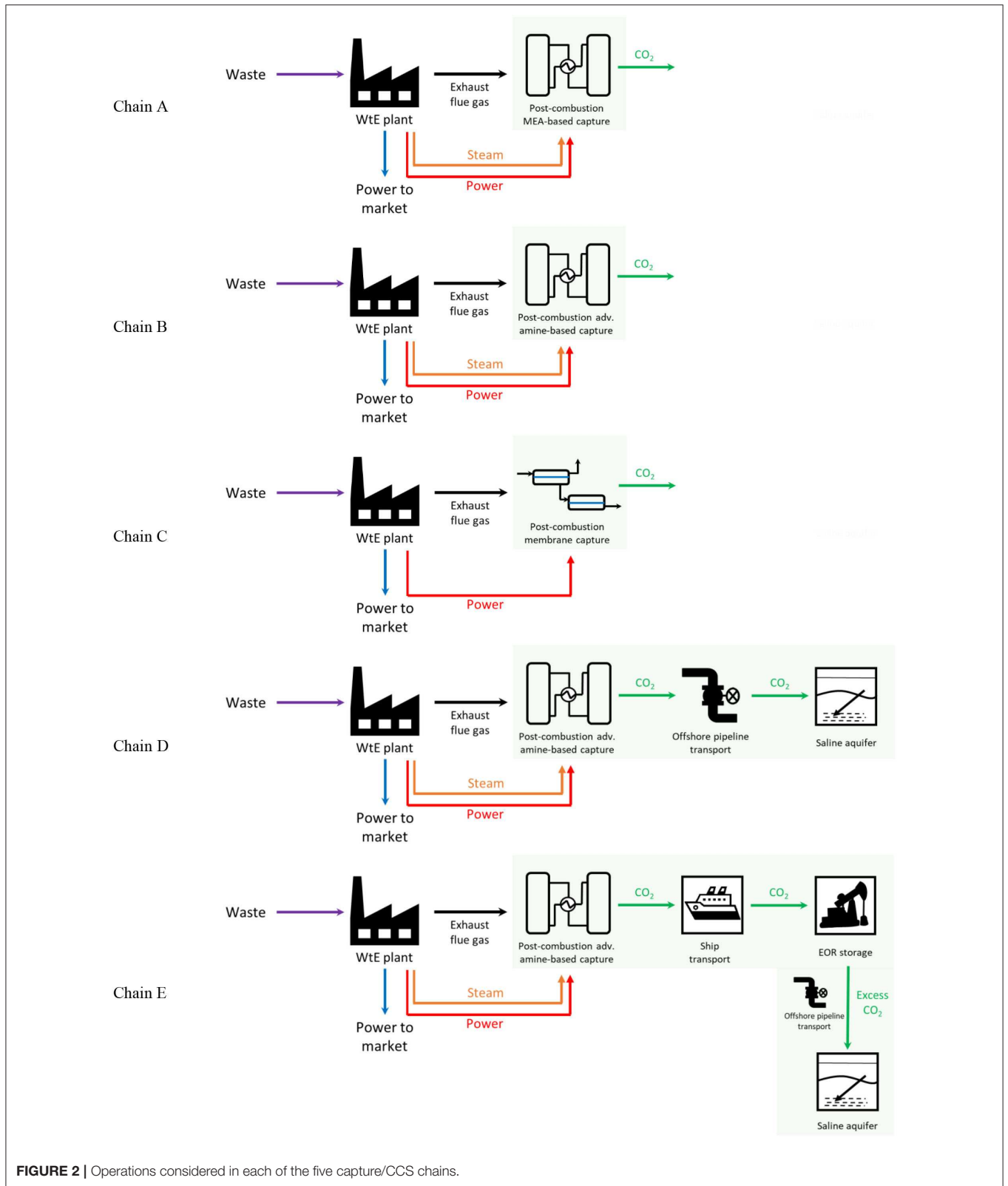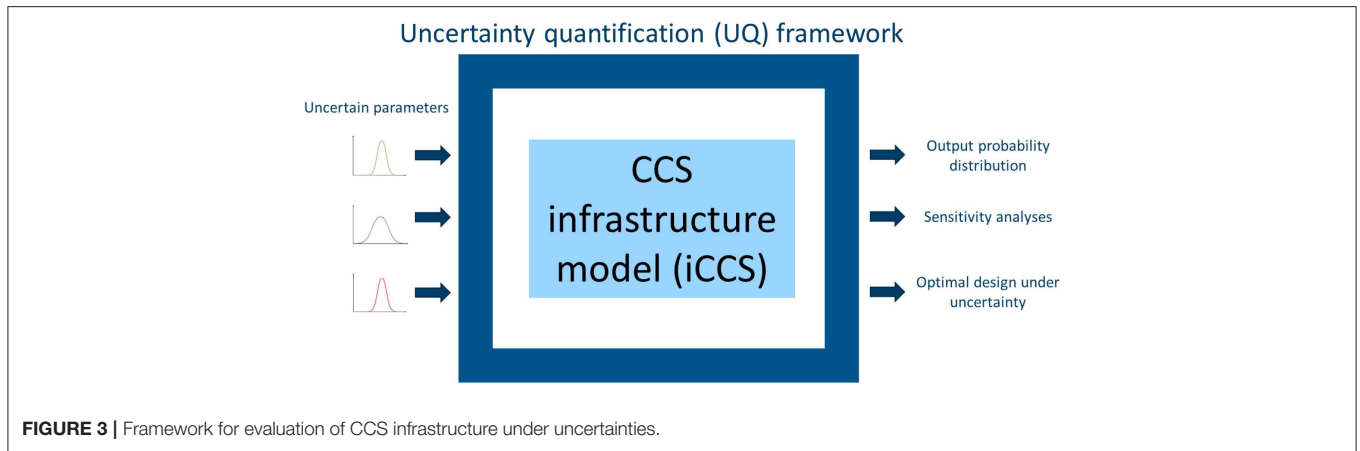**FIGURE 1 |** Locations of the waste-to-energy plant and potential storage sites.

FIGURE 2 | Operations considered in each of the five capture/CCS chains.

FIGURE 3 | Framework for evaluation of CCS infrastructure under uncertainties.

quantification framework in order to understand the impact of uncertainties on cost and design as shown in **Figure 3**. For a specified set of uncertainties, the integration of the uncertainty framework with the iCCS tool enables the possibility to generate performance probability distributions, multi-parameter global sensitivity analyses, and optimal design of the CCS chains under uncertainties.

WtE Plant and CCS Value Chain Modeling

The techno-economic performances of the WtE plant without CCS are considered to be known. The techno-economic modeling of the different CCS chain options are performed with the iCCS tool (Jakobsen et al., 2017). This tool is based on a flexible and modular approach in which each module is developed based on detailed technical and cost modeling. The different building blocks present in the library can be connected together to model the techno-economic performances of the targeted CCS value chain as illustrated in Jakobsen et al. (2017).

A summary of the content of each module and their technical and cost basis is available in Jakobsen et al. (2017). Details on the technical and cost basis of each of the modules of the iCCS tool can be found in previously published studies: post-combustion amine-based CO_2 capture (Husebye et al., 2012; Roussanaly et al., 2013a), post-combustion membrane-based CO_2 capture (Roussanaly et al., 2016, 2018; Roussanaly and Anantharaman, 2017), CO_2 transport via pipeline or ship (Roussanaly et al., 2013b, 2014), CO_2 storage in saline aquifer and EOR storage (Roussanaly and Grimstad, 2014). Key technical and cost aspects considered in the evaluation of each of the element of the WtE plant with the CCS chain are summarized in **Table 2** in the context of the present study.

Monte Carlo Simulations Modeling

Many real-world processes can be modeled in the form of a simple input-output relationship $y = f(x)$, where $x = (x_1, \ldots, x_n)$ describes all relevant inputs to the process, $y = (y_1, \ldots, y_n)$ describes all relevant outputs from the process, and the function f is the process model itself. For instance, in the case of MEA-based capture, the relevant input parameters x would include the flue gas concentration, the annual CO_2 capture capacity and average volume, utility prices, etc.; while the relevant

outputs would include the different utilities consumption, investment costs, and operating costs. The model f used to calculate these outputs can be implemented in many ways. Here, the iCCS tool is used to model each element of the chain where the relationships between the inputs and outputs are defined. These sets of models have been used in earlier work in a deterministic setting to evaluate the targeted outputs for the given set of inputs (Jakobsen et al., 2017), for sensitivity analyses (Roussanaly et al., 2013b), or for optimization purposes (Roussanaly and Anantharaman, 2017).

In this work, the CCS chain component models in iCCS are used for stochastic modeling with Monte Carlo simulation to take into account uncertainties in input data. Instead of assuming a given value for each input parameter x_n, a probability distribution $P(x_n)$ is used to describe each uncertain parameter. The simulation program then picks random values for each input from these distributions, feeds them into the process model f, and collects the results obtained for the process outputs y_n. After the simulation is complete, the results are used to estimate the probability distributions $P(y_n)$ for each output y_n. Due to the large amount of cases to be evaluated, stochastic modeling requires significantly more time than deterministic modeling. However, such an approach is crucial when looking at ex-ante system such as carbon capture and storage, as it can be used to better understand the impact of uncertainties on design, cost, and comparison of options. The principle of a Monte Carlo modeling framework is illustrated in **Figure 4**.

Oracle Crystal Ball is used as the stochastic modeling and optimization framework in the present study (2014). This program allows to set distribution type (normal, log-normal, uniform, etc.) and associated characteristics on input variables x_n, and generate an estimated probability distribution of output variables y_n, statistical distribution data and global sensitivity analyses. The program also enables optimization of an objective function both on a deterministic and a stochastic basis via the OptQuest function. The CO_2 avoidance cost is the key performance indicator used as the objective function to be minimized in this work. In the case of stochastic optimization, Crystal Ball is used to minimize the mean CAC of the distribution.

TABLE 2 | Key technical and cost characteristics considered in the evaluation of each element of the WtE plant with CCS chain.

Element of the chain	Modeling basis	Key technical and cost aspects
WtE plant without CCS	Plant key characteristics	• Municipal waste processing capacity: 70 t_{MSW}/h • Net power output: 40 MW • Climate impact: 1.684 tCO_2/MWh (Haaf et al., under review) • Share of biogenic emissions: 65% (Haaf et al., under review) • Cost of electricity: 80 €/MWh (Pour et al., 2018) • Peak flue gas mass flowrate: 453.3 t/h (Haaf et al., under review) • CO_2 molar content in flue gas: 10% (Haaf et al., under review) • Utilization rate: 85% with a sinusoidal yearly fluctuation varying between 70 and 100%
MEA-based CO_2 capture	iCCS	• CO_2 capture ratio: 90% • Conditions after capture: 1 bar and 40°C • Steam consumption: 3.9 GJ/tCO_2 (Haaf et al., under review) • Electric power consumption: 29 kWh/tCO_2 • Cooling water consumption: 45 m^3/tCO_2 • MEA make-up consumption: 1.5 kg_{MEA}/tCO_2
Advanced amine-based CO_2 capture	iCCS	• CO_2 capture ratio: 90% • Conditions after capture: 1 bar and 40°C • Steam consumption: 3.1 GJ/tCO_2 (Adams et al., 2017; Roussanaly et al., 2019) (−20% compared to MEA) • Electric power consumption: 29 kWh/tCO_2 • Cooling water consumption: 45 m^3/tCO_2 • Solvent make-up consumption: 1.5 $kg_{Solvent}$/tCO_2 • Investment compared to MEA: +10% (Adams et al., 2017; Roussanaly et al., 2019)
Membrane-based CO_2 capture	iCCS	• CO_2 capture ratio range: 50% to 90% • Conditions after capture: 1 bar and 40°C • Membrane CO_2/N_2 selectivity: 75 (Budhathoki et al., 2019) • Membrane CO_2 permeance: 15 m^3_{STP}/(m^2.h.bar) (Budhathoki et al., 2019) • Membrane module cost: 50 €/m^2 (Zhai and Rubin, 2013) • Membrane replacement over: 5 y (Zhai, 2019) • Membrane replacement cost: 10 €/m^2 (Zhai and Rubin, 2013)
Conditioning prior to offshore pipeline transport	iCCS	• Conditions after conditioning process: 200 bar and 40°C [European Technology Platform for Zero Emission Fossil Fuel Power Plants (ZEP), 2011b] • Electric power consumption: 99 kWh/tCO_2 • Cooling water consumption: 13 m^3/tCO_2
Conditioning prior to ship transport	iCCS	• Conditions after conditioning process: 6.5 bar and −50.3°C [European Technology Platform for Zero Emission Fossil Fuel Power Plants (ZEP), 2011b] • Electric power consumption: 107 kWh/tCO_2 • Cooling water consumption: 19 m^3/tCO_2
Offshore pipeline transport	iCCS	• Minimum pressure at the outlet of the pipeline: 60 bar [European Technology Platform for Zero Emission Fossil Fuel Power Plants (ZEP), 2011b] • No subsea rebooosting station due to prohibitive cost • Pipeline diameter optimized to minimize cost while meeting the minimum outlet pressure • Pipeline cost model based on Knoope et al. (2014)
Ship transport to an offshore site	iCCS	• Conditions after reconditioning process: pressure above 60 bar and temperature above 5°C • Ship investments, operating cost and fuel consumption are functions of ship capacity • Ship fuel cost: 332 €/t_{fuel} (Worldwide, 2017) • Ship capacity optimized to minimize cost
Saline Aquifer storage	iCCS	• Well injection rate: 0.8 $MtCO_2$/well/y [European Technology Platform for Zero Emission Fossil Fuel Power Plants (ZEP), 2011a] • Well cost: 21.8 M€/well (Jakobsen et al., 2017) • Liability cost: 1 €/tCO_2 [European Technology Platform for Zero Emission Fossil Fuel Power Plants (ZEP), 2011a]
CO_2 EOR storage	iCCS	• Well injection rate: 0.8 $MtCO_2$/well/y [European Technology Platform for Zero Emission Fossil Fuel Power Plants (ZEP), 2011a] • Well modification cost: 10.9 M€/well (Roussanaly and Grimstad, 2014) • Liability cost: 1 €/tCO_2 [European Technology Platform for Zero Emission Fossil Fuel Power Plants (ZEP), 2011a] • Average EOR response: 1.25 bbl_{oil}/tCO_2 (Roussanaly and Grimstad, 2014) • Oil economic value: 40 €/bbl (Roussanaly and Grimstad, 2014)
Overall plant with WtE with CCS	iCCS	• The levelized cost of electricity (LCOE) and CO_2 avoidance cost (CAC) as defined by Rubin et al. (2013) is used as key performance indicator to optimize and compare the different CCS options • The benefits of negative emissions, enabled by the capture of otherwise biogenic emissions, are included
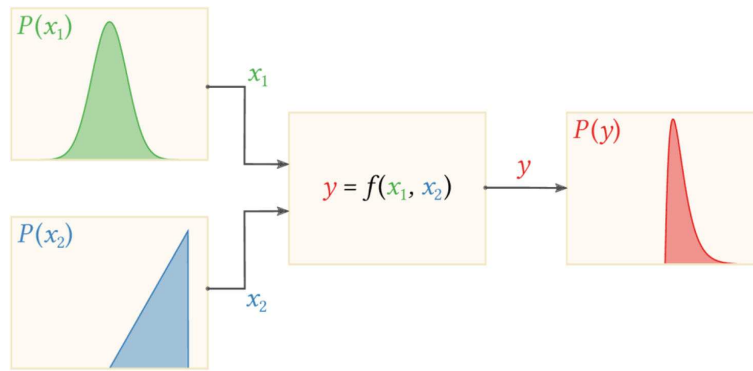
FIGURE 4 | Illustration of the principle of a Monte Carlo modeling framework. Random values for the inputs x_1 and x_2 are sampled from their probability distributions $P(x_n)$, the model f is evaluated for each random value and used to estimate the output distribution $P(y)$.
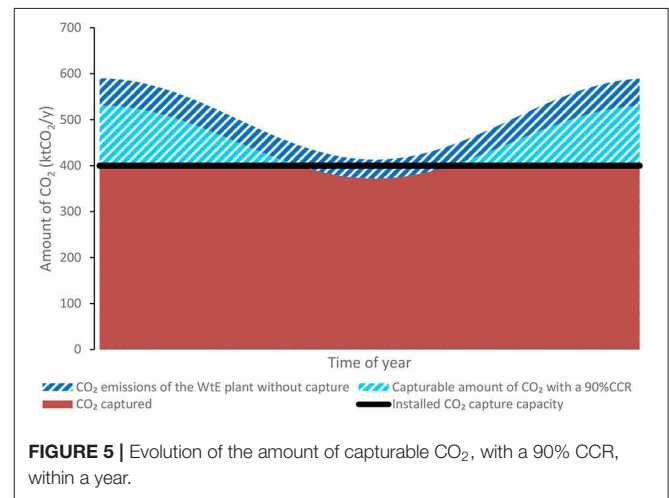
Uncertainties Considered and Fluctuations

Key elements of the evaluation of the impact of uncertainties are defining the uncertain parameters and their associated probability distribution. **Table 3** summarizes the uncertain parameters and probability distribution characteristics[4] for each of the value chain elements considered in the studies.

For investment costs (CAPEX[5]) along the chain, a beta type of uncertainty distribution is considered. This typically represents the uncertainties of the cost evaluation approaches associated with such projects, especially in the case of technologies with limited large scale experience (Bechtel Infrastructure Power and Corporation, 2018). Log-normal distributions are used for technical performances and prices to also account for the uncertainties in performances prediction, abnormal operation periods, unlikely events, sub-optimal performances during fluctuation periods. Furthermore, in the case of solvent-based CO_2 capture, possible worsening of performances over time associated with solvent degradation, prior to periodic solvent reclaiming, also leads to significant uncertainties on utilities consumptions.

For mature technologies (MEA-based capture, transport, storage), the investment costs consider a $-30\%/+50\%$ uncertainty range while a 10% standard deviation is considered on technical performances. However, higher uncertainties are considered for novel technologies (advanced amine-based and membrane-based captures) to reflect the lower level of current knowledge. In this case, the investment costs consider a $-50\%/+70\%$ uncertainty range while a 25% standard deviation is considered on technical performances.

Furthermore, in the case of membrane-based capture, uncertainties on the membrane characteristics (selectivity, permeance, and lifetime) are also included. Membrane properties are assumed to follow a min-extreme distribution in which the deterministic properties [selectivity of 75 and permeance of 15 m^3_{STP}.$(m^2$.h.bar)] are set as maximum values while the

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[4]An overview of the different types of probability distribution considered in this study is presented in Appendix A (**Supplementary Material**).
[5]CAPEX stands for capital expenditure.

FIGURE 5 | Evolution of the amount of capturable CO_2, with a 90% CCR, within a year.

properties of the Polaris membrane [selectivity of 50 and permeance of 6 m^3_{STP}/(m^2.h.bar)] (Merkel et al., 2010) are set as minimum values in order to represent the state of current technology development. The membrane module lifetime also considers a min-extreme distribution ranging from 1 to 7 years. The uncertainties in membrane properties can be due to manufacturing issues, inherent or environmentally induced degradation overtime, as well as uncertainties in properties achievable at industrial scale. Meanwhile, uncertainties in membrane module lifetime are due to limited experience on the impact of inherent or environmentally induced degradation overtime on the optimal amount of time between membrane module replacement.

Uncertainties in shipping fuel prices and oil economic value are due to uncertainties in future prices as well as potential fluctuations within a given year.

Beyond the above uncertainties, scenario-based uncertainties are also considered in some of the evaluations. For instance, normally distributed uncertainties on the amount of CO_2 coming from nearby industries and different uncertainty scenarios for CO_2 EOR storage are considered in some cases. More detail

TABLE 3 | Description of statistical distributions used in the present study.

Technology	Parameter	Distribution	Mean	Std. dev.	Comments
Capture (MEA)	CAPEX	Beta	102%	16%	*Min* = 70%, max = 150%, $\alpha = 2$, $\beta = 3$
	Electricity consumption	Log-normal	100%	10%	*Min* = 90%
	Solvent consumption	Log-normal	100%	10%	*Min* = 90%
	Steam consumption	Log-normal	100%	10%	*Min* = 90%
Capture (Advanced amine)	CAPEX	Beta	98%	24%	*Min* = 50%, max = 170%, $\alpha = 2$, $\beta = 3$
	Electricity consumption	Log-normal	100%	25%	*Min* = 90%
	Solvent consumption	Log-normal	100%	25%	*Min* = 90%
	Steam consumption	Log-normal	100%	25%	*Min* = 90%
Capture (Membrane)	CAPEX	Beta	98%	24%	*Min* = 50%, max = 170%, $\alpha = 2$, $\beta = 3$
	Electricity consumption	Log-normal	110%	25%	*Min* = 100%
	Membrane lifetime	Min-extreme	92%	18%	*Mode* = 100%, *scale* = 15%
	Membrane selectivity	Min-extreme	65.3	5.0	*Mode* = 67.5, *scale* = 4.5
	Membrane permeance	Min-extreme	11.1	2.1	*Mode* = 12.0, *scale* = 1.9
Conditioning (Pipeline)	CAPEX	Beta	102%	16%	*Min* = 70%, max = 150%, $\alpha = 2$, $\beta = 3$
	Electricity	Log-normal	100%	10%	*Min* = 90%
Conditioning (Ship)	CAPEX	Beta	102%	16%	*Min* = 70%, max = 150%, $\alpha = 2$, $\beta = 3$
	Electricity	Log-normal	100%	10%	*Min* = 90%
Transport (Pipeline)	CAPEX	Beta	102%	16%	*Min* = 70%, max = 150%, $\alpha = 2$, $\beta = 3$
	Uncertainty on amount from other CO_2 sources	Normal	100%	15%	This uncertainty is not used in all cases
Transport (Ship)	CAPEX	Beta	102%	16%	*Min* = 70%, max = 150%, $\alpha = 2$, $\beta = 3$
	Shipping fuel price	Log-normal	100%	10%	*Min* = 90%
Storage (No EOR)	CAPEX (Injection wells)	Beta	102%	16%	*Min* = 70%, max = 150%, $\alpha = 2$, $\beta = 3$
Storage (EOR, I)	EOR production	Normal	100%	10%	
	Oil economic value	Normal	100%	10%	
Storage (EOR, II)	EOR production	Normal	100%	10%	
	Oil economic value	Normal	100%	10%	
	Oil production scenario	Yes-No	–	–	50% chance for each of two scenarios

discussions on these uncertainties are take place in section Impact of Uncertainties on the Design and Cost of the WtE Plant with CCS.

In addition to uncertainties, the power output of the WtE plant and thus the flue gas mass flowrate is assumed to vary throughout the year. The emissions without CCS is considered to follow a sinusoidal profile with an annual average equivalent to 85% of the peak emission. With a capture ratio of 90%, the captured amount of CO_2 thus varies between 0.413 and 0.590 $MtCO_2$/y in the course of the year. Due to the temporal evolution of emissions, it is worth noting that an installed capacity below the peak flowrate (100% capacity) may be optimal, although this means not all emissions would be captured in this case as illustrated in **Figure 5**. While the optimal captured capacity is sought in some cases, a full-scale capture capacity is assumed in the result sections unless otherwise indicated.

RESULTS FOR THE WTE PLANT WITH CO_2 CAPTURE

Performances and Cost on a Deterministic Basis

This section illustrates the performances of the waste-to-energy plant without and with CO_2 capture on a deterministic basis, i.e.,

no uncertainty is considered. The key characteristics of the WtE plant without and with CO_2 capture[6] are presented in **Table 4**. The levelized cost of electricity and CO_2 avoidance cost are illustrated in **Figure 6**.

In all cases aiming at capturing 90% of the emissions, implementing CO_2 capture results in significant losses in the net power output of the plant (between 55 and 70% lower than without capture). This is primarily due to the very high amount of CO_2 captured (90% of both biogenic and non-biogenic emissions) and the low efficiency of the plant. However, as large quantities of biogenic CO_2 emissions are captured, large quantities of negative CO_2 emissions are enabled, especially in the solvent-based cases: from 0.157 tCO_2/MWh with membrane to 0.716 tCO_2/MWh with advanced amine.

The low CO_2 concentration in the flue gas (10%vol CO_2) results in extremely high power losses for membrane-based capture with 90% capture ratio. Considering partial capture can significantly reduce this energy penalty. Indeed, a CO_2 capture ratio of 50% (i.e., a reduction of 45% in the amount of CO_2 captured), leads to a power loss associated with CO_2
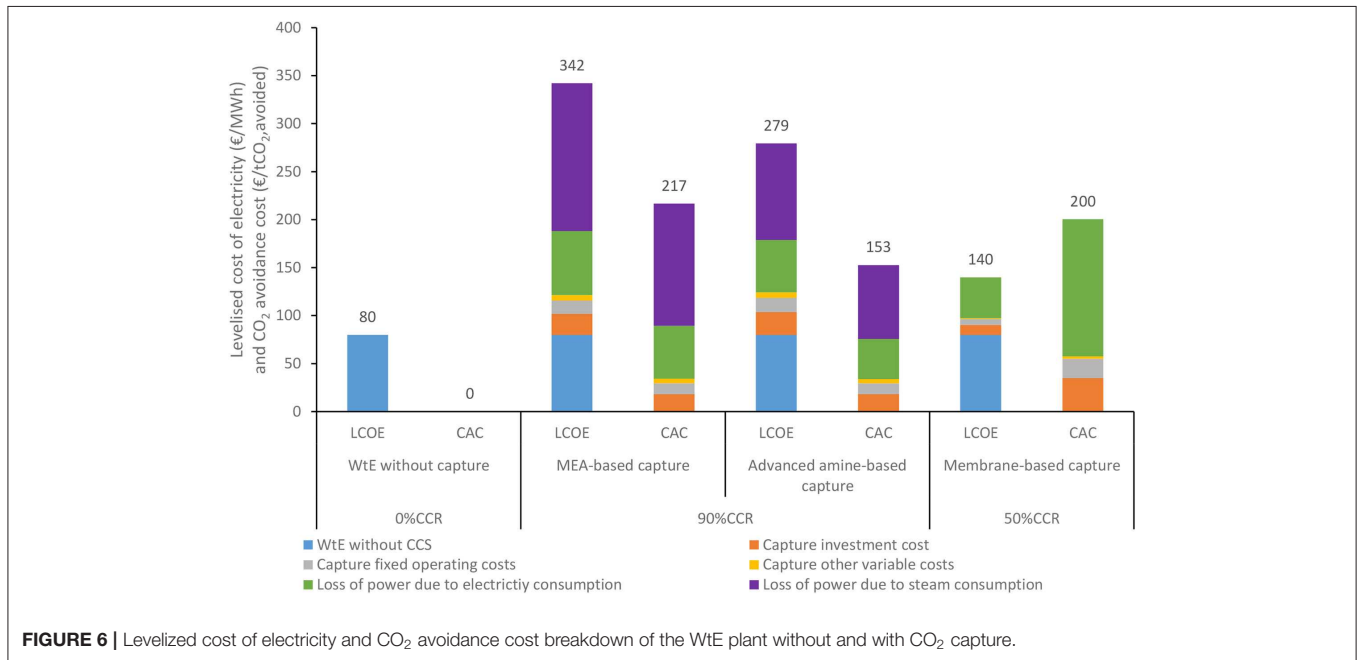
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[6]Conditioning prior to a pipeline transport is here included, even if transport and storage cost are not part of the performance and cost estimate in this section.

TABLE 4 | Key characteristics of the WtE plant without and with CO_2 capture.

Capture scenario	WtE without capture	MEA-based capture	Advanced solvent-based capture	Membrane-based capture		Units
CCR	0	90	90	90	50	%
CO_2 capture capacity	–	531	531	531	295	$ktCO_2$/y
CO_2 capture volume	–	451	451	451	251	$ktCO_2$/y
Steam consumption	–	1.76	1.41	–	–	10^6 GJ/y
Electricity consumption	–	58	58	244	106	10^6 kWh/y
Power loss due to CO_2 capture	–	25.8	22.2	32.82	14.24	MW
Net power output	40	14.2	17.8	7.2	25.8	MW
Total CO_2 emissions (biogenic and non-biogenic)	1.684	0.474	0.378	0.938	1.308	tCO_2/MWh
Non-biogenic CO_2 emissions	0.589	0.166	0.132	0.328	0.458	tCO_2/MWh
Total CO_2 emissions avoided (biogenic and non-biogenic)	–	1.210	1.306	0.746	0.376	tCO_2/MWh
Non-biogenic CO_2 emissions avoided	–	0.423	0.457	0.261	0.132	tCO_2/MWh
Net negative emissions[a]		0.620	0.716	0.157	−0.213[b]	tCO_2/MWh
Membrane area	–	–	–	38,128	79,751	m^2
Membrane replacement	–	–	–	7,626	15,950	m^2/y
MEA consumption	–	0.69	0.69	–	–	10^6 kg_{MEA}/y
Levelized Cost Of electricity	80	342	279	620	155	€/MWh
CO_2 avoidance cost	–	217	153	730	200	€/tCO_2, avoided

[a]Net negative emissions calculated by subtracting the non-biogenic CO_2 emissions of the plant without CO_2 capture from the avoided biogenic and non-biogenic CO_2 emissions of the plant with CO_2 capture.
[b]No negative emission is enabled in this case.

FIGURE 6 | Levelized cost of electricity and CO_2 avoidance cost breakdown of the WtE plant without and with CO_2 capture.

capture 55% lower than at 90% CCR. However, a significant drawback of this option is that there are no net negative emissions. The total CO_2 emissions (biogenic and non-biogenic) captured correspond to 73% of the non-biogenic CO_2 emissions without capture, which is slightly below the CO_2 avoided ratio (∼80%) obtained in the case of coal and gas power plants with CCS (Anantharaman et al., 2011).

From a cost perspective, the implementation of CO_2 capture at 90% CCR results in LCOEs[7] from 279 to 620 €/MWh, depending

[7]It is important to note that the LCOE calculation does not consider any financial credit for the negative emissions enabled and that at least part of the additional cost related to CCS may be charged to household producing the waste being treated by the plant.

FIGURE 7 | CO_2 avoidance cost distribution of the WtE plant with CO_2 capture.
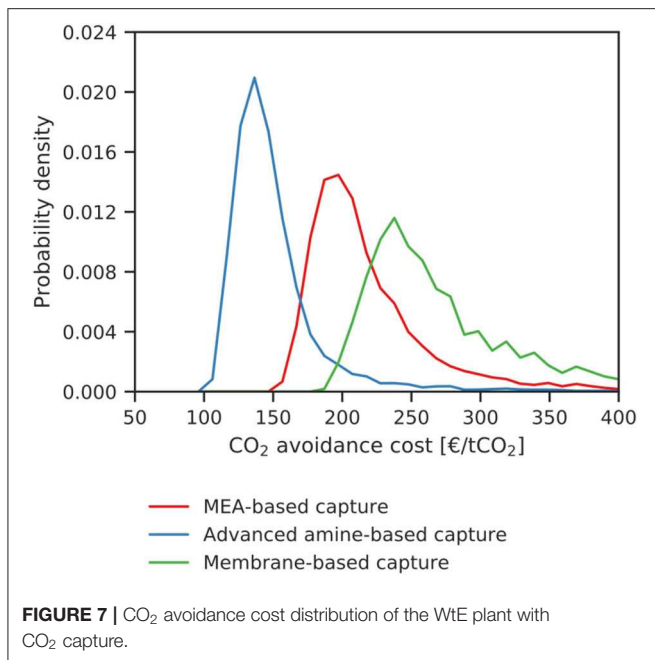
TABLE 5 | Key characteristics and global sensitivity analysis[a] of the CO_2 avoidance cost distribution (€/tCO_2, avoided) of the WtE plant with CO_2 capture.

Parameter	MEA	Advanced amine	Membrane
Deterministic	217	153	200
Mean	220	151	280
P2.5	168	115	203
P25	189	130	233
Median	206	142	258
P75	234	159	304
P97.5	368	261	490
Sensitivity analysis			
Capture—CAPEX	34%	59%	5.7%
Capture—Steam consumption	79%	56%	–
Capture—Electricity consumption	8.5%	9.9%	1.8%
Capture—Solvent consumption	2.2%	3.3%	–
Capture—Membrane selectivity	–	–	54%
Capture—Membrane permeance	–	–	−85%
Capture—Membrane lifetime	–	–	−5.9%
Conditioning—CAPEX	7.3%	6.5%	2%
Conditioning—Electricity consumption	33%	27%	1.8%

[a]A positive value means that an increase in the parameter lead to a higher CAC, while a negative value means lower CAC.

on the capture options, while the LCOE of the WtE without capture was estimated to be 80 €/MWh. The solvent-based capture technologies yield the best performances. The LCOE of the MEA-based capture is 342 €/MWh, while the advanced amine-based capture, with an LCOE of 279 €/MWh, lead to a 19% reduction compared to MEA. The membrane-based capture at 90% CCR leads to an LCOE that is nearly 7 times higher than the case without capture. This is due to the extremely large reduction in net power output of the plant in this case. However, the LCOE in the 50% CCR case is 93% higher than the case without CO_2 capture. The increase in LCOE is considerably lower in the 50% CCR because less CO_2 is captured, and the capture process is more energy efficient. In all capture cases, the power losses associated due to steam and/or electricity consumption for the capture contributes to most of the LCOE increase (74–84%).

Similar trends are observed for the CAC. Except for the 90% CCR membrane capture case, the CAC ranges between 153 and 217 €/tCO_2, avoided depending on the capture option considered and is mainly due to the loss of power associated with CO_2 capture. Compared to the MEA-based CO_2 capture, the advanced amine and the 50% CCR membrane capture options enable a cost reduction of, respectively, 30 and 8%. While the CACs evaluated here are higher than those of typical power and industrial plants, they are on the low range of cost estimates for negative emission technologies such as bioenergy with CCS (BECCS) and direct air capture (DAC), which are in the range 50-250 €/tCO_2, avoided and 100–2,000 €/tCO_2,captured, respectively (Bui et al., 2018). Furthermore, compared to BECCS, the negative emissions enabled by CCS from the WtE are due to the biological part of the waste thus overcoming the shortcoming typically associated with BECCS (availability, land use, waster user, fertilizer consumption). CCS from WtE plants could thus be a cost-efficient option to deliver the negative

emissions often identified as crucial to meet the ambitions of the Paris Agreement.

Overall, the high LCOEs obtained emphasize the importance of a financial credit for the negative emissions enabled by installing CO_2 capture in WtE plant and a higher fee charged for the decarbonization of the treatment of municipal waste which is the main purpose of a WtE plant. For this reason, the LCOE with CCS is not deemed to be a good key performance indicator for decarbonization of WtE and only the CAC is considered in subsequent sections.

Finally, the fact that most of the increase in LCOE and CAC is due to a decrease in plant power output emphasizes that capture technologies with low energy penalty for the CO_2 concentration considered will be key to reach cost-efficient CO_2 capture from WtE.

Impact of Uncertainties on CAC and Comparison of the Different Technologies

The impact of uncertainties on the CAC for the three capture technologies considered is shown in **Figure 7**. The statistical distributions of the different parameter uncertainties were presented in **Table 3** while the CO_2 avoidance cost distribution is presented in **Table 5**.

The CAC cost distribution for all technologies are skewed to the right, with the skew being most prominent for the membrane case. The MEA case CAC distribution shows a mean value 220 €/tCO_2, avoided, while the first quartile, the median and third quartile are 189, 206, and 234 €/tCO_2, avoided, respectively. The mean CAC is very similar to the deterministic CAC of 217 €/tCO_2, avoided. In the case of the advanced amine CAC distribution, the mean CAC is 151 €/tCO_2, avoided, while the

first quartile, the median and third quartiles are 130, 142, and 159 €/tCO$_2$, avoided, respectively. The mean CAC in the advanced amine case is very similar again to the deterministic CAC of 153 €/tCO$_2$, avoided. While the median and mean CAC of the advanced amine case are lower than those of the MEA case, the advanced amine CAC distribution shows a slightly higher relative spread[8], indicating greater uncertainty.

The membrane case CAC distribution has a mean value of 280 €/tCO$_2$, avoided. The median value is 258 €/tCO$_2$, avoided while the first and third quartiles are 233 and 304 €/tCO$_2$, avoided, respectively. Both the mean and median CACs are significantly greater than the deterministic CAC of 200 €/tCO$_2$, avoided, calculated with no uncertainties. The deterministic evaluation assumed a membrane with good properties (selectivity and permeance). However, the simulations with uncertainty use membranes with selectivity and permeance ranges below the ones of the deterministic evaluation as shown in **Table 4**. This leads to higher costs than in the deterministic case as can be seen in the CAC distribution of the membrane case. Also, although the membrane case CAC distribution shows the smallest spread of the three cases, it is worth noting that its cost distribution is flatter meaning that wide range of cost is similarly probable.

From a technology selection or comparison perspective, given the results of the deterministic analysis, the advanced amine showed the most promise, followed by the membrane and then MEA cases. However, with the inclusion of uncertainties, while the advanced amine shows the largest potential to have a low CAC, the order is reversed between the membrane and MEA cases. The MEA will more likely have a lower CAC than the membrane case.

A global sensitivity analysis was also performed as part of the study based the uncertainty distributions considered. The global sensitivity of the CAC to the different parameters for the three capture technology cases as shown in **Table 5**. For the MEA and advanced amine cases, steam consumption followed by the CAPEX and then the electricity consumption for conditioning process have the largest impact on the CAC. The effects of electricity consumption in the capture plant and the solvent consumption are minimal. The effects of these different parameters can be inferred from the breakdown of the CAC for the deterministic case shown in **Figure 7**, where loss of power in the WtE plant due to steam consumption in the CO$_2$ capture plant is the largest contributor.

In the case of the membrane-based capture process, the membrane properties (selectivity and permeance) have the largest impact on the CAC. The membrane permeance and CAC are negatively correlated in that as the membrane permeance increases the CAC decreases. The membrane permeance has a sizeable impact on the CAC, while the membrane lifetime has a small impact. The remaining parameters do not have much of an impact.

Impact of Uncertainty in CO$_2$ Emission Penalties on the Design and Cost

In the earlier section, results of the impact of uncertainties on the CAC of the three CO$_2$ capture technologies were presented. Another relevant question is how uncertainties affect the design or the optimal capacity of the capture process. The optimal capacity of the capture process does not change with the inclusion of uncertainties for the three capture processes evaluated. The optimal capacity for the solvent cases—MEA and advanced amine—is 78%, which is the same as the value evaluated for the deterministic case. For the membrane case, the optimal capacity is 50%, similar to the deterministic case.

Appendix B in **Supplementary Material** shows the CO$_2$ avoidance cost breakdown and share of avoided emissions for the three CO$_2$ capture processes as a function of the installed capacity factor. As can be seen from the figures for the solvent processes, the optimum CAC is around 80% capacity factor. The reason for this is that the CAPEX contribution to the CAC decreases with increasing capacity factor, while the loss of power due to steam consumption and electricity consumption, the main contributors to the CAC, increase slightly with increasing capacity factor. The optimal capacity is close to the utilization rate (85%) of the WtE plant.

For the case of membranes, the electricity contribution to the CAC increases significantly with increasing capacity factor even though the CAPEX contribution to the CAC decreases slightly (see Appendix B in **Supplementary Material**). With the electricity consumption being the largest contributor to the CAC, this results in the CAC increasing with increasing capacity factor. The optimal capacity is thus at 50% capacity factor.
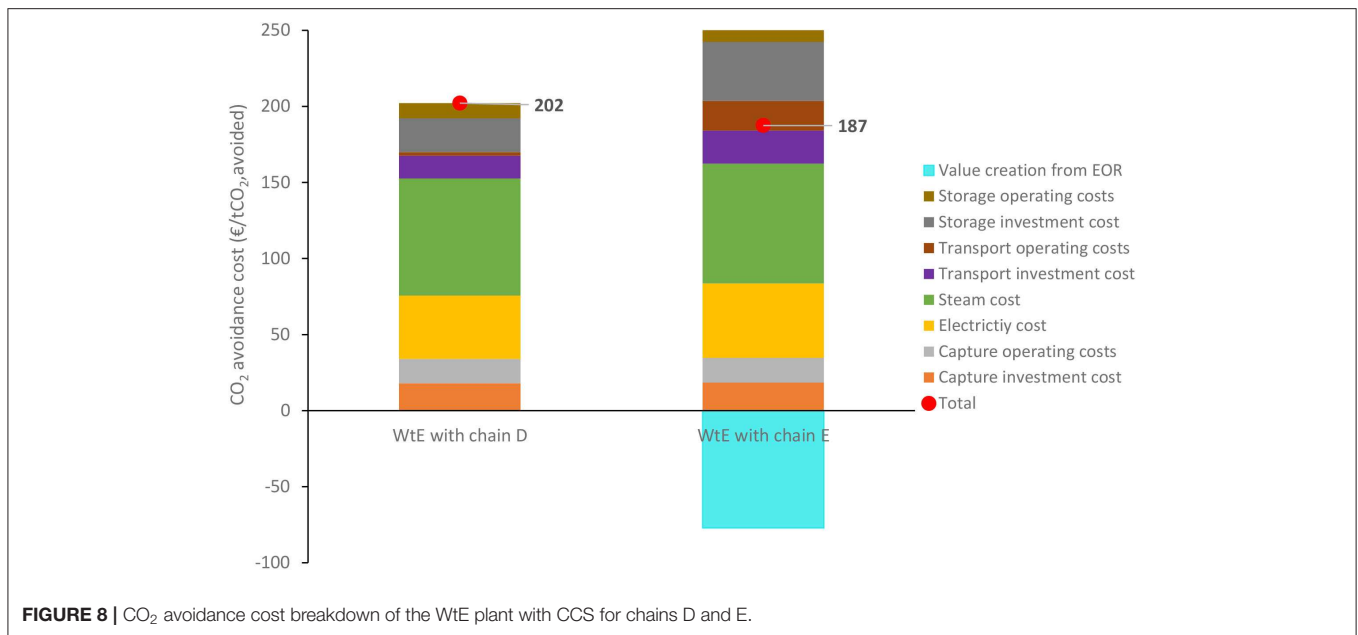
RESULTS FOR THE WTE WITH CO$_2$ CAPTURE, TRANSPORT, AND STORAGE

Design and Costs on a Deterministic Basis

The design and cost evaluation of reducing the CO$_2$ emissions of the WtE plant, including the full CCS chain is presented in this section. For both CCS chains considered (chains D and E), the CO$_2$ capture options are based on the advanced amine. This section shows the performance of the WtE plant with CCS on a deterministic basis, similar to the CO$_2$ capture chains in section Performances and Cost on a Deterministic Basis. While the technical performances of the WtE including the entire CCS chain are similar to the WtE plant with CO$_2$ capture, the CAC increases as a result of the inclusion of CO$_2$ transport and storage and is illustrated in **Figure 8**.

For chain D, based on CO$_2$ transport via a shared 100 km pipeline and storage in a nearby shared saline aquifer (Chain D), a CAC of 202 €/tCO$_2$, avoided is obtained. Most of the increase compared to the case with only CO$_2$ capture is linked with the storage costs (two-thirds of the increase). A pipeline diameter of 8.625″ was found[9] to be cost-optimal based on the CO$_2$ emissions captured from the WtE and nearby industries.

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[8]The relative spread is here defined by comparing the percentile range P97.5 – P2.5 to the mean value.

[9]Pipeline diameter and ship capacity are selected in the iCCS tool to minimize costs.

FIGURE 8 | CO_2 avoidance cost breakdown of the WtE plant with CCS for chains D and E.

Chain E considers a 250 km transport via a shared ship to an EOR storage site. Due to the gradual reduction in the amount of CO_2 which can be injected in the EOR storage over time, a nearby saline aquifer was considered to store the excess CO_2. The profiles of CO_2 injected in the EOR storage and saline aquifer over the years is presented in Appendix C (**Supplementary Material**). As a result of the longer transport distance and the two storage facilities, the transport and storage costs are higher in chain E than chain D. However, the value creation associated with the oil production of the EOR storage significantly offsets this cost increase, leading to a CAC for chain E of 187 €/MWh (7% lower than chain D). An optimal ship size of 8,000 m^3 was evaluated for the transport to the EOR storage, based on transport capacity and distances, while an optimal pipeline diameter of 5.5625″ was identified for transport from the EOR storage site to the nearby aquifer.

Impact of Uncertainties on the Design and Cost of the WtE Plant With CCS

This section discusses the impact of different uncertainty scenarios on the CO_2 avoidance cost, design and comparison of WtE plant with CCS chains D and E. Three groups of uncertainties are considered. First the impact of "internal" uncertainties, referring to uncertainties not directly linked to the decision of an agent, is considered in section Impact of Internal Uncertainties. The additional impact of "external" uncertainty linked directly through the decision of an agent, here considered to be amount of CO_2 coming from nearby industries, is then considered in section Impact of Uncertainty in the Amount of CO2 Coming from Nearby Industries. Finally, the impact of the uncertainty in the EOR response of chain E, in addition to internal uncertainties, is investigated in section Impact of the EOR Response on Comparison of Chain.

While these three groups of uncertainties are investigated in the three following sections, the key characteristics and global sensitivity analyses are gathered in **Table 6**.

Impact of Internal Uncertainties

The "internal" uncertainties of the two chains (CAPEX of the different parts of the chain, steam consumption, EOR production, oil economic value, etc. but no uncertainty on the amount of CO_2 coming from nearby industries) are first compared, as illustrated in **Figure 9**. The chain D shows a mean CAC value of 201 €/tCO_2, avoided, while the first quartile, the median and the third quartiles are 176, 189, and 208 €/tCO_2, avoided, respectively. For chain E, the mean value is 186 €/tCO_2, avoided, while the first quartile, the median and the third quartile are 159, 175, and 196 €/tCO_2, avoided, respectively. In both cases, the mean CAC value of the distributions matches the deterministic value, which implies that chain E remains in average cheaper than chain D even once uncertainties are taken into account. Although chain E results in more uncertain costs, as can be observed from the wider spread, the CAC associated with the key percentiles (P2.5, P25, Median, P75, P97.5) of chain E are always lower than for chain D and is thus more cost-efficient even when internal uncertainties are taken into account.

Impact of Uncertainty in the Amount of CO_2 Coming From Nearby Industries

The impact of uncertainty in the flow of CO_2 coming from nearby industries, in addition to the internal uncertainties, is also analyzed. When doing so, the re-optimization of the ship size and pipeline diameters is considered.

Once the uncertainty on flow from nearby industries included, the mean CAC of chains D and E are 206 and 190 €/tCO_2, avoided, respectively, as illustrated in **Figure 9**. This corresponds to an increase of 4–5 €/tCO_2, avoided compared to the case

TABLE 6 | Key characteristics and global sensitivity analysis of the CO_2 avoidance cost distribution (€/tCO_2, avoided) of the WtE plant with CCS chains D and E under the different uncertainty scenarios.

Parameter	Chain D, no flow uncertainty	Chain D, with flow uncertainty	Chain E, no flow uncertainty	Chain E, with flow uncertainty	Chain E, yes–no oil uncertainty
Deterministic	202	206	187	190	–
Mean	201	206	186	190	200
P2.5	159	162	134	135	140
P25	176	180	159	162	170
Median	189	194	175	179	189
P75	208	213	196	202	213
P97.5	333	348	329	334	344
Sensitivity analysis					
Capture—CAPEX	52%	50%	47%	45%	41%
Capture—Steam consumption	59%	59%	55%	54%	52%
Capture—Electricity consumption	11%	11%	9.9%	8.7%	9.6%
Capture—Solvent consumption	3.1%	3.1%	2.6%	3.8%	3.2%
Conditioning—CAPEX	5.8%	5.8%	11%	10%	9.6%
Conditioning—Electricity consumption	30%	29%	31%	30%	28%
Amount of CO_2 coming from other sources	–	−15%	–	−18%	–
Pipeline—CAPEX	9.9%	11.6%	0.2%	0.4%	0.1%
Ship—CAPEX	–	–	11%	12%	9.3%
Ship—Fuel price	–	–	0.4%	1.6%	0.2%
Injection wells—CAPEX	4.1%	5.2%	7.1%	5.0%	5.5%
Oil economic value	–	–	−26%	−21%	−18%
EOR production	–	–	−22%	−23%	−15%
Oil production scenario	–	–	–	–	−37%

without uncertainty on the CO_2 flow from nearby industries. Although this cost increase is small related to the overall CAC, this correspond to an 10–15% increase for the transport and storage contribution to the CAC for the two chains. It is important to note that the design of the CCS chain changes when the uncertainty on the CO_2 flow from nearby industries are included. The optimal pipeline diameters of chains D and E increase to 10.75″ and 6.625″, respectively, while the ship capacity increases to 10,500 m³. The main reason for this is that the transport infrastructure design points identified in section Design and Costs on a Deterministic Basis have maximum capacities[10] of 1.77 and 1.68 MtCO₂/y, respectively for the two chains D and E. As a result, without redesign the CCS infrastructure would be unable to ensure transport and storage in 35 and 1.8% of the cases for chains D and E, respectively.
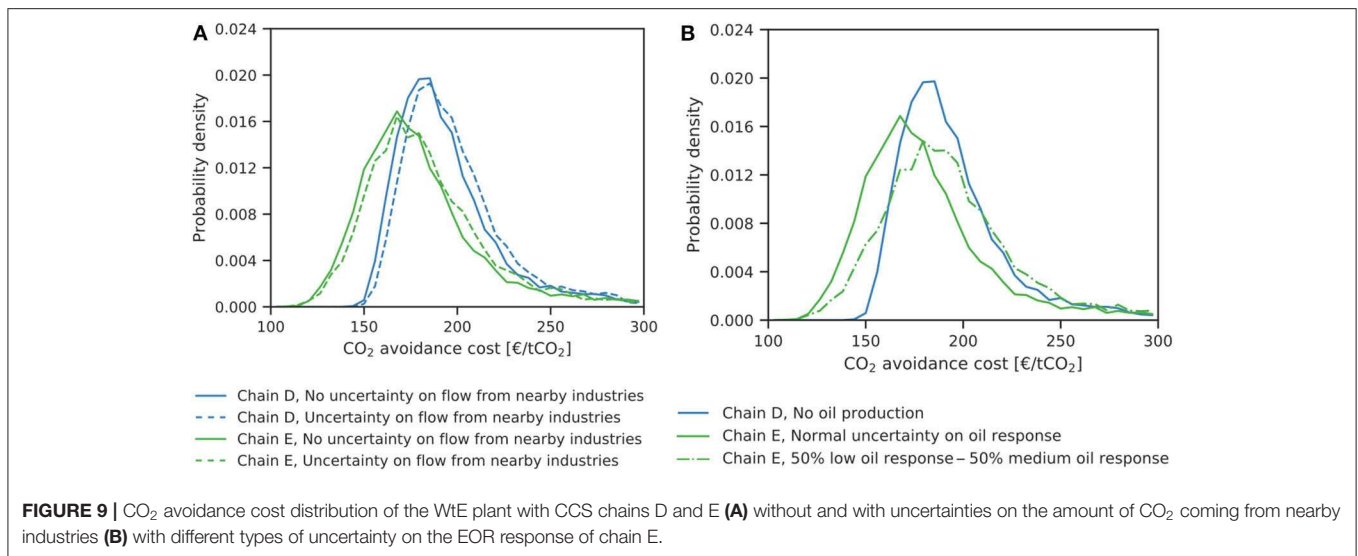
For chain D, the first quantile, the median and the third quartile are 180, 194, and 213 €/tCO_2, avoided respectively. Meanwhile, for chain E, the first quantile, the median and the third quartile are 162, 179, and 202 €/tCO_2, avoided, respectively. Thus, despite an increase in CAC in both cases, it is worth noting that the CAC profiles remain similar in shape compared to the case without uncertainty on the flow from nearby industries.

Impact of the EOR Response on Comparison of Chain

In addition to the uncertainties discussed above, a key uncertainty in the case of an CO_2 EOR project is the response to CO_2 injection. Although CO_2 EOR developments are often based on oil fields in the secondary or ternary recovery phase, which is thus better known than a completely new development, significant uncertainties remain. Thus, the impact of the EOR response uncertainties on the costs of chain E and its comparison to chain D is investigated. Two EOR uncertainty cases are considered. First, as earlier, a normally distributed uncertainty on the oil production is considered. This case corresponds to a situation in which the storage response is expected to be very well-known. A second case in which the EOR response is more uncertain is considered. This scenario considers an additional "Yes-No" type of uncertainty in which the EOR response has a 50% probability of being identical to the first uncertainty scenario (medium response scenario) and 50% likelihood to be 39% lower (low response scenario). In both cases, the other uncertainties present along the chain are considered, except uncertainties on the amount of CO_2 coming from nearby industries. The impact of these uncertainties on the CAC of these chains E are presented and compared to chain D in **Figure 9**.

As before, the different probability distributions are skewed to the right, although the second chain E case is less skewed and more spread than the other two. Compared to the case of a normally distributed uncertainty on the EOR response, chain

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[10]Considering a utilization rate of 100%.

FIGURE 9 | CO_2 avoidance cost distribution of the WtE plant with CCS chains D and E **(A)** without and with uncertainties on the amount of CO_2 coming from nearby industries **(B)** with different types of uncertainty on the EOR response of chain E.

E with the "Yes-No" type of uncertainty results in higher CAC as the revenues associated with the CO_2 EOR storage injection are reduced. As a result, the mean CAC in the second case is 10 €/tCO_2, avoided (5%) higher than in the normally distributed case. Thus, the second EOR uncertainty case results in an on par CAC of the chain E and chain D (0.5% difference, while chain E is 7.5% cheaper on a deterministic basis) thus potentially impacting the selection of the option transport and storage strategy.

CONCLUSIONS

The objective of this study was to investigate the optimal design of carbon capture and storage from a waste-to-energy plant under uncertainties. Using an in-house techno-economic CCS assessment tool combined with an uncertainty quantification framework, the case of CCS from a hypothetical 40 MW waste-to-energy plant located in Norway was considered.

When the different capture options are compared on a deterministic basis, the advanced amine option yield the best performances with a CO_2 avoidance cost of 153 €/tCO_2, avoided, followed by the membrane process based on partial capture (200 €/tCO_2, avoided) and MEA-based capture (217 €/tCO_2, avoided). While these CACs are higher than those of typical power and industrial plants, they are on the low range of cost estimates for negative emission technologies such as BECCS and DAC. CCS from WtE plants could thus be a cost-efficient option to deliver the negative emissions often identified as crucial to meet the ambitions of the Paris Agreement.

Once technical and cost uncertainties are taken into account, the advanced amine-based capture remains the best option, however the MEA-based capture outperforms the membrane process, as the membrane properties considered in the deterministic comparison are optimistic when considering the current status of membrane development. However, the stochastic optimization performed showed that the uncertainties considered do not impact the optimal capture capacity in this case.

The full CCS chain perspective was then included through two chain options: a nearby offshore saline aquifer or an offshore CO_2 EOR storage located further away but which could add an additional economic benefit to the project. The EOR-based chain would lead to the best performances both on a deterministic basis and when different uncertainty scenarios are considered. However, as a shared transport and storage infrastructure is considered, uncertainties on the amount of CO_2 coming from nearby industries led to a different optimal design of the chain (pipeline diameter and ship capacity). Finally, uncertainties on the EOR response to CO_2 injection significantly reduce the potential of the CO_2 EOR-based chain and can result in cases in which the saline aquifer-based chain would be optimal.

These results show that taking into account uncertainties, beyond the traditional sensitivity analysis commonly used in the literature, can enable a deeper understanding of the CO_2 avoidance cost, better technology comparison and better CCS chain designs. Given the ex-ante nature of CCS, this could be crucial in unlocking more cost-efficient CCS implementations. However, to obtain meaningful results, further work to better understand and characterize underlying uncertainties will also be required.

DATA AVAILABILITY STATEMENT

All datasets generated for this study are included in the article/**Supplementary Material**.

AUTHOR CONTRIBUTIONS

All authors listed have made a substantial, direct and intellectual contribution to the work, and approved it for publication.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenrg.2020.00017/full#supplementary-material

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