Navigating Deep Uncertainty in Carbon Capture Technologies

An Investigation of CCS and CCU Investments at a Swedish Waste-to-Energy Plant using Robust Decision Making

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Abstract

With Sweden and the EU aiming to reach net-zero carbon dioxide emissions by 2045 and 2050, the interest in carbon capture technology such as Carbon Capture and Storage (CCS) and Carbon Capture and Utilisation (CCU) is on the rise, not least in hard-to-abate sectors such as waste incineration. Several Swedish waste management actors are now considering CCS or CCU, among them Tekniska Verken i Linköping AB (TvAB), who are the owners of the waste-to-energy plant Gärstadverken. However, there are many financial uncertainties related to CCS and CCU investments, such as uncertainty in transport and storage costs, potential revenue from CCU products and CCS carbon credits, electricity price development, and more. As a result, evaluating the profitability of CCS and CCU projects is challenging.

To provide TvAB with additional decision support, this study adopts Robust Decision Making (RDM) to examine what conditions could favour or disfavour a carbon capture investment at Gärstadverken. The alternatives examined are CCS and CCU with the production of electronic Sustainable Aviation Fuel (eSAF). Through discussions with TvAB representatives and literature research, a model of the investment decisions was created using the open-source Python library Rhodium. This model was evaluated in 120 000 futures, and the results were analysed using Sobol sensitivity analysis, Classification and Regression Trees (CART) and the Patient Rule Induction Method (PRIM).

The simulation results show that for CCS, the most important factor is the price TvAB can receive for their carbon credits, even when emission allowances are expensive and a large fraction of the emitted CO_2 is biogenic. Transport and storage costs and carbon capture investment costs are also shown to be important factors.

For CCU, the most crucial factor is the price that TvAB charges for their eSAF. However, CCU could be favourable at lower eSAF prices if the electrolyser costs are reduced and/or if electricity and emission allowance prices are low. However, it should be noted that the limited study scope resulted in many simplifications – notably when modelling the development of eSAF and carbon credit prices. As such, more efforts should be put into investigating the development of the eSAF and carbon credit markets.

Keywords: CCS, CCU, eSAF, Waste-to-Energy, RDM, DMDU

Sammanfattning

Givet Sveriges och EU:s mål att nå nettonollutsläpp av koldioxid år 2045 respektive 2050 ökar intresset för koldioxidinfångningstekniker som Carbon Capture and Storage (CCS) och Carbon Capture and Utilisation (CCU), inte minst inom sektorer såsom avfallsförbränning där utsläppen är svåra att minska. Flera svenska aktörer inom avfallshantering överväger nu CCS eller CCU, däribland Tekniska Verken i Linköping AB (TvAB) som äger avfallsförbränningsanläggningen Gärstadverken. Samtidigt finns det många ekonomiska osäkerheter kopplade till investeringar i CCS och CCU, till exempel osäkerhet kring transport- och lagringskostnader, potentiella intäkter från CCU-produkter och koldioxidkrediter samt framtida elpriser. Detta gör det utmanande att bedöma lönsamheten av CCS- och CCU-projekt.

För att ge TvAB ytterligare stöd i sitt beslut använder denna studie Robust Decision Making (RDM) för att undersöka vilka förutsättningar som kan gynna eller missgynna en investering i koldioxidinfångning vid Gärstadverken. De alternativ som undersöks är CCS samt CCU med produktion av electronic Sustainable Aviation Fuel (eSAF). Med hjälp av litteraturstudier och samtal med representanter från TvAB byggdes en modell för investeringsbesluten i det öppna Python-biblioteket Rhodium. Modellen utvärderades i 120 000 olika framtidsscenarier och resultaten analyserades med hjälp av Sobols känslighetsanalys, Classification and Regression Trees (CART) och Patient Rule Induction Method (PRIM).

Resultaten visar att den viktigaste förutsättningen för CCS är priset på koldioxidkrediter – även när utsläppsrätter är dyra och en stor andel av den infångade koldioxiden är biogen. Även transport- och lagringskostnader samt koldioxidinfångningsanläggningens investeringskostnad är betydande faktorer.

För CCU är den viktigaste faktorn priset TvAB kan ta för sin eSAF. Dock kan en investering i CCU även vara gynnsam vid lägre eSAF-priser om priset på elektrolysörer minskar och/eller om el- och utsläppsrättspriserna är låga. Samtidigt bör det nämnas att studiens begränsade omfång innebar många förenklingar – särskilt vid modelleringen av prisutvecklingen för eSAF och koldioxidkrediter. Därför bör utvecklingen av marknaderna för eSAF och koldioxidkrediter studeras vidare.

Nyckelord: CCS, CCU, eSAF, Avfallsförbränning, RDM, DMDU

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Wila Lindberg, August 2025

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List of Abbreviations

i. Abbreviation Appearing in *Part I: Introduction* and *Part II: Literature Review*

AEC – Alkaline Electrolysis Cell

BECCS – Bio-Energy Carbon Capture and Storage

CAPEX – Capital Expenditures

CC – Carbon Capture

CCS – Carbon Capture and Storage

CCT – Cost Conscious Transition

CCU – Carbon Capture and Utilisation

CCU/S – Carbon Capture and Utilisation & Carbon Capture and Storage

CO_2 – Carbon Dioxide

CRC – Carbon Credit

DAP – Dynamic Adaptive Planning

DMDU – Decision Making under Deep Uncertainty

EASA – European Union Aviation Safety Agency

eSAF – electronic Sustainable Aviation Fuel

ESF – Energy Security First

ESR – EU Effort Sharing Regulation

ETS – Emission Trading System

FT-process – Fischer-Tropsch based process

H_2 – Hydrogen gas

HPC – Hot Potassium Carbonate

IEA – International Energy Agency

MEA – Monoethanolamine

OPEX – Operational Expenditures

PEMEC – Proton Exchange Membrane Electrolysis Cell

RDM – Robust Decision Making

RSF – Renewable Sustainability First

SAF – Sustainable Aviation Fuel

SEA – Swedish Energy Agency

SOEC – Solid Oxide Electrolysis Cell

SOW – State of the World

TNO – The Netherlands Organisation for Applied Scientific Research

TvAB – Tekniska Verken Linköping AB

VCM – Voluntary Carbon Market

WAM – With Additional Measures

WEM – With Existing Measures

WtE – Waste-to-Energy

ii. Abbreviations Appearing in *Part III: RDM Analysis -Method*

Abbreviations not used in calculations

CAPEX – Capital Expenditures

CART – Classification and Regression Tree

CC – Carbon Capture

CCS – Carbon Capture and Storage

CCT – Cost Conscious Transition

CCU – Carbon Capture and Utilisation

CCU/S – Carbon Capture Utilisation and Storage

CRC – Carbon Credits

ESF – Energy Security First

eSAF – electronic Sustainable Aviation Fuel

ETS – Emission Trading System

LHS – Latin Hypercube Sampling

NPV – Net Present Value

NPV – Net Present Value

OPEX – Operational Expenditures

PRIM – Patient Rule Induction Method

RDM – Robust Decision Making

RSF – Renewable Sustainability First

$\mathbf{S_{1,i}}$ – first-order Sobol sensitivity index of parameter *i*

$\mathbf{S_{2,ij}}$ – second-order Sobol sensitivity index of parameters *i* and *j*

SEA – Swedish Energy Agency

SOW – State of the World

$\mathbf{S_{T,i}}$ – total order Sobol sensitivity index of parameter *i*

TvAB – Tekniska Verken i Linköping AB

WAM – With Additional Measures

WEM – With Existing Measures

Abbreviations used in calculations

Abbreviation	Unit	Description
A	/year	Annuity factor of carbon capture and electrolyser facilities
$bCO_2(t)$	t/year	Biogenic CO_2 captured at Gärstadverken annually
C_0	SEK	Carbon Capture CAPEX 2030
$CAPEX_{CC}(t_{inv})$	SEK	Investment cost of carbon capture facility
$CAPEX_{H2,MW}(t_{inv})$	SEK/MW	Investment cost of electrolyser per installed MW
$CAPEX_{H2,spec}(t_{inv})$	SEK	Investment cost of electrolyser
$cElec_{CC}$	MWh/year	Electricity consumed by carbon capture facility annually
$C_{H2,MW}$	MW	Electrolyser capacity
C_{RR}	-	Carbon Capture CAPEX Reduction Rate
DR	-	Discount rate
E_0	SEK	Electrolyser CAPEX 2030
E_{RR}	-	Electrolyser CAPEX Reduction Rate
$fCO_2(t)$	t/year	Fossil CO_2 captured at Gärstadverken annually
F_{out}	kg/year	Annual amount of syncrude produced
$F_{revenue}$	SEK/year	Annual revenue form fuels produced from CCU
NPV_{CCS}	SEK	Net present value of investing in CCS
NPV_{CCU}	SEK	Net present value of investing in CCU
$NPV_{n.i.}$	SEK	Net present value of not investing
$pCC(t, t_{inv})$	SEK/year	Annual costs of carbon capture
$pCRC$	SEK/t_{CO2}	Price of carbon credits per tonne CO_2
$pElec(t)$	SEK/MWh	Electricity price
$peSAF$	SEK/kg	Price TvAB charge for their eSAF
$pETS(t)$	SEK/t_{CO2}	Emission fee per tonne CO_2
$pH_2(t, t_{inv})$	SEK/year	Annual costs related to H_2 production
$pNaphtha$	SEK/kg	Price of naphtha
$pSteam$	SEK/year	Annual steam costs related to carbon capture facility
$pSynth$	SEK/kg	Costs of synthesising syncrude (mixture of eSAF and naphtha)
pWP	SEK/year	Annual water and power grid costs related to electrolysis
r	-	Interest rate
R_{CCS}	SEK	Regret of investing in CCS as compared to not investing
R_{CCU}	SEK	Regret of investing in CCU as compared to not investing
T	years	Useful lifetime
t_0	year	Starting year of CAPEX calculation (year 2030)
tCO_2	t/year	Amount of CO_2 captured per year
t_{inv}	year	Investment year
TS	SEK/t_{CO2}	Transport and storage costs per tonne CO_2
Y_{eSAF}	-	Yield of eSAF, i.e. fraction of syncrude being eSAF
$Y_{naphtha}$	-	Yield of naphtha, i.e. fraction of syncrude being naphtha

iii. Abbreviations Appearing in *Part IV: RDM Analysis – Results*

C0 – Carbon capture CAPEX year 2030 [SEK]

CAPEX – Capital Expenses

CART – Classification and Regression Tree

CC – Carbon Capture

CCS – Carbon Capture and Storage

CCT – Cost Conscious Transition

CCU – Carbon Capture and Utilisation

CRC – Carbon Credits

CRR – Carbon capture CAPEX annual price reduction rate

ERR – Electrolyser CAPEX annual price reduction rate

eSAF – electronic Sustainable Aviation Fuel

ESF – Energy Security First

fCO2_2030 – Fraction fossil CO_2 out of annual captured CO_2 year 2030 [t_{CO2}/year]

fCO2_2060 – Fraction fossil CO_2 out of annual captured CO_2 year 2060 [t_{CO2}/year]

pCRC – Price of carbon credits [SEK/t_{CO2}]

pElec_2030 – Mean electricity price year 2030 [SEK/MWh]

pElec_dt – Electricity price volatility

pElec_vPlat – Value of electricity price plateau [SEK/MWh]

pElec_yPlat – Year electricity price plateau is reached [Year]

peSAF – Price of eSAF [SEK/kg_{eSAF}]

PRIM – Patient Rule Induction Method

R_{CCS} – Regret of investing in CCS as compared to not investing

R_{CCU} – Regret of investing in CCU as compared to not investing

RSF – Renewable Sustainability First

S_2 – Second-order Sobol sensitivity index

S_T – Total Sobol sensitivity index

TS – Transport and storage costs [SEK/t_{CO2}]

vi. Abbreviations Appearing in *Part V: Discussion*

CAPEX – Capital Expenses

CC – Carbon Capture

CCS – Carbon Capture and Storage

CCT – Cost Conscious Transition

CCU/S – Carbon Capture Utilisation and Storage

CRC – Carbon Credits

EASA – European Union Aviation Safety Agency

eSAF – electronic Sustainable Aviation Fuel

ESF – Energy Security First

ETS – Emission Trading System

NPV – Net Present Value

PRIM – Patient Rule Induction Method

RDM – Robust Decision Making

RSF – Renewable Sustainability First

SOW – State of the World

TS – Transport and Storage

TvAB – Tekniska Verken i Linköping AB

VCM – Voluntary Carbon Market

WtE – Waste-to-Energy

Part I: Introduction

Carbon Capture and Storage (CCS) and Carbon Capture and Utilisation (CCU) present an opportunity for Waste-to-Energy (WtE) plant actors to reduce or make use of the carbon dioxide emissions generated from waste incineration. Among WtE-actors, Tekniska Verken Linköping AB (TvAB) is now considering incorporating carbon capture at their WtE facility Gärstadverken. The captured carbon dioxide (CO_2) could then be stored underground or utilised as a raw product, e.g. when producing electronic sustainable aviation fuel (eSAF). However, there are many uncertainties related to the economics of CCS and CCU, which makes it difficult for actors like TvAB to make an investment decision. To aid TvAB in their decision, this study applies Robust Decision Making (RDM) – a framework for decision making under deep uncertainty (DMDU), meaning that there are numerous possible outcomes, or the future is unknown (Marchau, Walker, Bloemen & Popper 2019). RDM presents a numerical approach to evaluate strategies in the presence of deep uncertainty and can give insights about what conditions favour one decision over another (Marchau et al. 2019). This study applies RDM to examine five potential CCU and CCS (CCU/S) investment strategies at Gärstadverken, namely:

1. Investing in CCS year 2030
2. Investing in CCS year 2040
3. Investing in CCU year 2030 and using the CO_2 for eSAF production
4. Investing in CCU year 2040 and using the CO_2 for eSAF production
5. Not investing at all

Moreover, to support the RDM analysis, a narrative literature review is performed. For a description of the thesis outline, see Table 1.

Table 1. Description of the outline of the thesis.

Part	Pages	Brief Description
Introduction	1-7	This part includes a short background on the rising interest in CCU/S technologies, their relation to WtE-plants, and the issue of uncertainties related to CCU/S investments. It also gives an introduction to the DMDU and RDM frameworks, followed by a description of research motivations and objectives.
Literature Review	7-17	The purpose of this part is to provide information about CCU/S investments by first giving an overview of CCS, CCU, and eSAF and then briefly describing uncertainties related to CCU/S costs and revenues.
RDM Analysis – Method	18-39	This part is dedicated to the RDM analysis itself, starting with descriptions of tools used in RDM analysis, how the RDM framework is implemented, and how the investment decision is modelled.
RDM Analysis – Results	40-53	Here, the results from the analysis are presented and commented on.
Discussion	54-57	In this section, the research questions are addressed based on results from the RDM analysis and literature review. Limitations of the study are also highlighted, followed by suggestions for future research and conclusions drawn from the study.

1. Background

1.1 Rising Interest in CCS and CCU Technologies

To reach the Paris agreement's aim of limiting global warming below 2ºC, there have to be great reductions in greenhouse gas emissions. In the EU, the goal is to reach net zero emissions of carbon dioxide (CO_2, one of the main contributors to global warming) by 2050 (European Commission n.d. a). Similarly, Sweden has the goal of reaching net-zero by 2045 (Swedish Environmental Protection Agency 2025). However, there are sectors that currently have a limited capability of reducing their emissions, for example, the agriculture (Swedish Energy Agency [SEA] 2023a) and aviation sector (International Energy Agency [IEA] 2023). As such, carbon capture technologies are considered necessary to fulfil the goal of net zero emissions (IEA 2023; SEA 2023a). These are technologies that capture carbon dioxide to either store it long-term (CCS) or use it in or as a product where it can replace virgin CO_2 (CCU) (SEA 2023a).

In the case of CCS, it clearly has the potential to limit global warming as it prevents CO_2 from entering the atmosphere. Moreover, if the captured CO_2 originates from biogenic material, CCS provides negative emissions (SEA 2023a). This makes CCS a key feature in Sweden's strive towards net-zero since negative emissions can be used to offset unavoidable emissions (SEA 2023a).

CCU, on the other hand, offers the potential to substitute virgin CO2 – for instance, in fuel production (SEA 2023a). One of the fuels that can be produced from CCU is electronic sustainable aviation fuel, eSAF (also referred to as power-to-liquid fuel). As a response to the aviation sector's heavy dependence on fossil fuels, the EU has through the act *ReFuelEU Aviation* introduced a blending mandate of synthetic sustainable aviation fuels (such as eSAF) which is estimated to cause a significant rise in eSAF demand (Grimme 2023). In short, there exists a clear interest in CCU/S technology, both in the EU and in Sweden.

1.2 Strong Interest for CCU/S in the Waste Incineration Sector

Waste-to-Energy plants (WtE) are facilities where waste is incinerated to produce electricity and heat. In 2023, about 6.6 million tonnes of waste were handled by 35 Swedish WtE plants to produce 17.3 TWh of heat and 2.2 TWh of electricity (Avfall Sverige 2023). Tekniska Verken i Linköping AB (TvAB) is the owner of the WtE facility Gärstadverken which in 2024 collected 559 406 tonnes of waste (Tekniska Verken i Linköping AB [TvAB] 2024) and produces about 1500 GWh of heat and 300 GWh of electricity annually (TvAB n.d. b). One main advantage of WtE is that it prevents waste from being landfilled (SEA 2023b) while providing heat and electricity. On the other hand, considerable amounts of CO_2 are emitted in the incineration process. At Gärstadverken, about 600 000 tonnes of CO_2 are emitted annually (Alvin 2025).

Today, out of the waste received at WtE plants, about 50% is fossil (SEA 2023b). Incineration of this waste generates fossil CO_2 emissions - about 90% being a result of burning plastic (SEA 2023b). There are several possible measures to reduce plastic waste, including restricting plastic products on the market, improving recycling, and sorting at the inlet. Nevertheless, even if plastic is sorted out at the inlet, there are still plastics that cannot be recycled (Fridahl, Lundberg & Nehler 2022). Together with the amounts of plastic present in society today, plastic waste streams are expected to remain for some time to come (Fridahl et al. 2022). Burning this plastic would then make sure it is not landfilled (SEA 2023b). In order to meet net-zero goals, the emissions from burning this plastic must be handled in some other way, which is where CCU/S technology presents possible solutions. The Swedish Energy Agency even describes the development of CCS and CCU as critical for the future of WtE, pointing out that CCS at WtE plants is a must to reach net-zero CO_2 emissions (SEA 2023b). In other words, CCU/S technologies are expected to be introduced in the Swedish waste system.

For WtE actors, CCU/S could also present economic opportunities. One such driver is that Swedish WtE plants are part of the EU Emissions Trading System (ETS) (SEA 2023b). As of today, WtE actors have to pay a fee proportional to the mass of fossil CO_2 emitted, which could be avoided if caught via CCS (SEA 2023b). Moreover, since the waste is partially biogenic, CCS at a WtE plant would generate negative emissions, and thereby carbon credits (CRCs), which, for example, could be sold on a voluntary carbon market (Hansen & Jensen 2023). Meanwhile, through CCU, the captured CO_2 is recycled into a product providing a source of income.

As of today, several Swedish energy companies are looking at the possibility of adopting CCU/S. Sysav in Malmö and Renova in Gothenburg have taken orientation decisions to have CCS or CCU operating at their WtE plants by 2030 (Sysav n.d.; Renova 2024), Stockholm Exergi is performing studies on integration of CCS at their WtE plants in Högdalen and Brista (Stockholm Exergi n.d.), and in October 2024, the company Öresundskraft received a 54-million-euro support to invest in CCS at their WtE plant Filbornaverket, with the final investment decision being expected in 2025 (Öresundskraft 2024). In Linköping, TvAB has investigated the feasibility of incorporating a CCS or CCU unit at Gärstadverken (TvAB n.d. a). All this shows that there is a strong interest among WtE owners to invest in CCU/S technology. However, for actors like TvAB, there are questions regarding what conditions are required to make a CCU/S project profitable.

1.3 Uncertainty in CCU/S Makes it Difficult to Determine Profitability

CCU/S projects are complex as they involve advanced processes, infrastructure, and logistics, but could also require the investor to enter immature markets such as the CRC and eSAF markets. As a result, multiple parameters could induce uncertainty regarding the costs and revenues of CCU/S projects. Several studies have mapped risks and uncertainties related to CCU/S investments, showing that there are both technical, financial, political, and social uncertainties (Storrs, Lyhne & Drustrup 2023; Lee, Chun, Roh, Heo & Lee 2023; Kourosh Mahjour & Faroughi 2023). Examples include uncertainties regarding capital and operational expenses (Kourosh Mahjour & Faroughi 2023), revenues from CRCs or CCU products (Hansen & Jensen 2023; Lee et al. 2023), and development of ETS and electricity prices (Lamberts-Van Assche & Compernolle 2022b), to name a few.

Apart from being complex, CCU/S investments are also capital- and energy-intensive (Kourosh Mahjour & Faroughi 2023; Lamberts-Van Assche & Compernolle 2022b), long-term, and irreversible, meaning that uncertainties could pose great risks to investors. Given the risks, it is essential for investors to navigate among the many and complex uncertainties of CCU/S when deciding whether to invest or not. This makes the process of evaluating the profitability of a CCU/S project even more challenging.

Nevertheless, there are several methods to take uncertainties into consideration when performing a CCU/S feasibility study. Expert opinion would be a qualitative way to handle uncertainties (Kourosh Mahjour & Faroughi 2023), whereas quantitative ways include sensitivity analysis, scenario analysis, probabilistic uncertainty analysis, pedigree analysis, and pseudo statistical approach, to name a few (Lamberts-Van Assche & Compernolle 2023a; Boongaling Agaton 2021; Hu & Zhai 2017; van der Spek et al. 2020)

1.4 The DMDU and RDM Approach

1.4.1 DMDU

Another approach to handle the many uncertainties of CCU/S is Decision Making under Deep Uncertainty (DMDU). DMDU is a collection of approaches and computational tools to generate support to decision-makers when faced with so-called deep uncertainty. Deep uncertainty arises when there are many possible or unknown futures, system models, and system outcomes. In other words, they emerge in situations where it is difficult to produce reliable predictions and models, and when uncertainties are hard to characterise. (Marchau, Walker, Bloemen & Popper 2019)

Although the goal of DMDU is to give decision support, it is not meant to point out what the best decision is directly. Instead, DMDU aims to (comprehensively) present and give perspectives on the problem so that decision-makers can make good use of the available information. It does so by showing risks and opportunities of different strategies and uncovering trade-offs between them. (Marchau et al. 2019)

Figure 1 (Marchau et al. 2019) illustrates for what types of problems DMDU is deemed applicable. Generally, it is situations where uncertainty is deep, the problem is complex (e.g. the outcomes of choosing one strategy over another are not apparent), and where there are many ways to form a strategy (corresponding to many policy options in the figure).

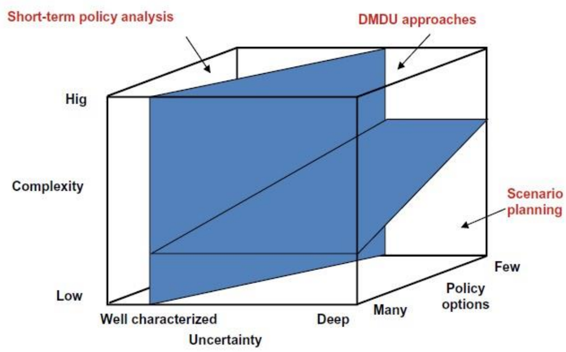


Figure 1. Diagram showing under what conditions various decision-making tools are appropriate. Based on Dewar (2006), as adapted by Marchau et al. (2019) in "Decision Making under Deep Uncertainty – From Theory to Practice". Licensed under CC BY 4.0.

1.4.2 RDM

One of the DMDU-methods is Robust Decision Making (RDM) – a computational method where the idea is to evaluate strategies over a large number of possible futures quantitatively and, in that way, find strategies that work well across many scenarios, meaning they are robust. (Marchau et al. 2019). RDM could also be used to identify vulnerabilities and critical scenarios of different strategies (Marchau et al. 2019). The steps of the method are presented in Figure 2.

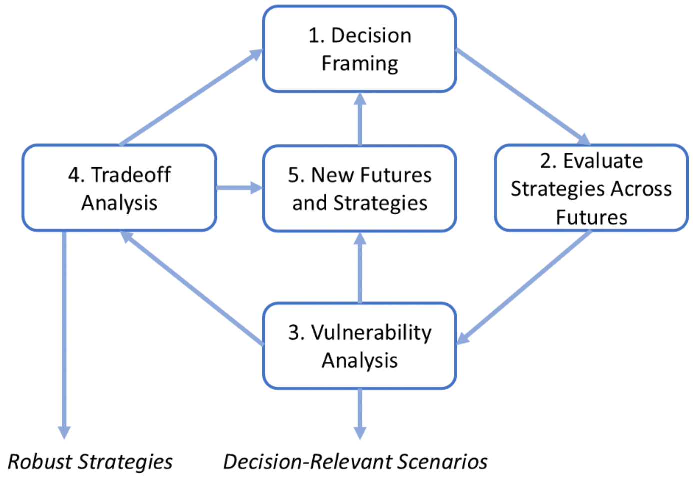


Figure 2. The main steps of the Robust Decision Making (RDM) approach. Adapted by the author from a figure in Marchau et al. (2019), originally by Lempert et al. (2013).

In short, the process starts with decision makers framing the problem, the solutions and the uncertainties (step 1). The main components of the RDM-analysis are then commonly summarized in an XLRM-table (Marchau et al. 2019). (This table summarises the uncertain factors (X), the options available to the decision makers (L), the decision makers' goals as measured by performance metrics (M), as well as how the uncertainties and options are related to the goals (R).)

Next, a model of the system is constructed where a selection of the parameters are appointed as uncertainties. By varying the value of the uncertainties, multiple futures (referred to as states of the world, SOWs) can be sampled. Since the point of RDM is to stress-test the examined strategies, a diverse set of futures should be sampled, each of them treated as "equally likely" (in contrast to e.g. probabilistic uncertainty analysis where futures are assigned probabilities). (Marchau et al. 2019)

The performances of the strategies are then evaluated in each future (step 2), and the results are analysed in search for weaknesses and strengths, such as trade-offs between strategies or circumstances that could cause a strategy to fail (steps 3 and 4). (There are various tools available to perform such analysis, of which three are described in section 8. *Tools of RDM analysis*.) The insights from the analysis are then presented to the decision maker(s) who develop the decision framing by, for instance, adding other uncertainties or creating new strategies to be tested (steps 5 and 1). From here, the process is repeated, making RDM an iterative method. (Marchau et al. 2019)

It is worth noting that RDM works with a set of strategies that are pre-defined by experts and decision-makers. Thus, in contrast to DMDU approaches such as Dynamic Adaptive Planning (DAP), RDM does not aim to generate completely new solutions. Another key concept in RDM is adaptive planning. The idea is to both identify the vulnerabilities of a strategy and ways to recognise when these risks are approaching. This enables decision-makers to plan for the future and take proactive decisions. (Marchau et al. 2019)

RDM has been applied to various fields, examples being policy development within carbon removal, fishery, water management, and transport (Miro et al. 2021; Engholm & Kristoffersson 2024; Conradt et al. 2024). However, to the author's knowledge there is only one previous RDM study done within the field of CCU/S. In the study *A robust investment* *decision to deploy bioenergy carbon capture and storage—exploring the case of Stockholm Exergi*, Oscar Stenström et al. perform an RDM analysis on the decision of employing bio-energy CCS (BECCS) or not at a bio-energy heat power plant in Stockholm (Stenström, Khatiwada, Levihn, Usher & Rydén 2024). The study uses the Python library Rhodium to model the costs and revenues related to investing in BECCS or not investing (Stenström et al. 2024).

2. Research Motivation

To answer the question whether RDM could aid TvAB in their decision to deploy CCS, CCU, or neither at Gärstadverken, one could consider Figure 1, which describes what problems DMDU approaches are suited for (Marchau et al. 2019). Generally, it is situations where:

a) there are deep uncertainties

b) the problem is complex (e.g. the outcomes of choosing one strategy over another are not apparent),

c) there are many policy options, i.e. many ways to form a strategy.

Starting with a), CCU/S projects involve a multitude of uncertainties, some of which could be considered deep uncertainties. Regarding b), the issues related to CCS and CCU are multifaceted. With many parameters involved, the outcome of choosing CCU/S over not investing, or choosing CCS over CCU, is not apparent, which makes the problem complex.

Lastly, as for c), although TvAB are faced with multiple decisions regarding choice of technology, CO_2 capturing capacity, time of investment etc., the complexity of CCU/S together with the limited scope of this study results in the analysis containing few options apart from investing or not. On the other hand, as Figure 1 illustrates, DMDU can be applicable even when the number of examined strategies is few, provided that uncertainties are deep and the system is complex. As such, RDM is deemed an appropriate approach to this investment decision. This is further supported by the findings of Stenström, who performs an RDM analysis on the decision of employing bio-energy CCS (BECCS) (Stenström et al. 2024).

For TvAB, the analysis could contribute to a deeper understanding of the mechanisms of CCU and CCS – how the investment responds to various changes in uncertain parameters, and under what conditions the investments are vulnerable. As for scientific contribution, to the author's knowledge, there are no previous studies performing RDM analysis on a CCU investment, nor on a CCS investment at a waste incineration plant. Thus, this study will not only contribute with another RDM analysis to the CCU/S field, but also with insights on how RDM can be used in the context of WtE and CCU.

3. Main Objectives and Aims (Research Questions)

The purpose of this report is to use the RDM framework to investigate the decision of investing in CCS, CCU, or neither at Gärstadverken. The study will take a financial point of view, meaning that aspects like the environmental performance of CCU/S lie outside the study scope. Moreover, although several products can be made from CCU, this study only investigates the production of eSAF.

This study aims to, with the help of RDM, provide insights into the conditions for a CCU/S project to be preferred over not investing. More specifically, the research questions are:

- Under what conditions will an investment in CCS at Gärstadverken be preferable or not preferable financially in comparison to not investing?
- Under what conditions will an investment in carbon capture and eSAF production at Gärstadverken be preferable or not preferable financially in comparison to not investing?

4. Research Design

As mentioned in section 1.4.2 *RDM*, the RDM procedure is an iterative process where the model development and analysis of results are performed multiple times. This is shown in Figure 3, which provides a simplified overview of the procedure adopted in this study. As can be seen from the figure, the provision of input data and model construction is partly done with the help of literature analysis. The literature study aims to identify factors that could affect a CCS or CCU investment at Gärstadverken, as well as identify potential parameter values for the RDM model. Moreover, it serves as a means to gain further understanding about the investment and the limitations of the model.

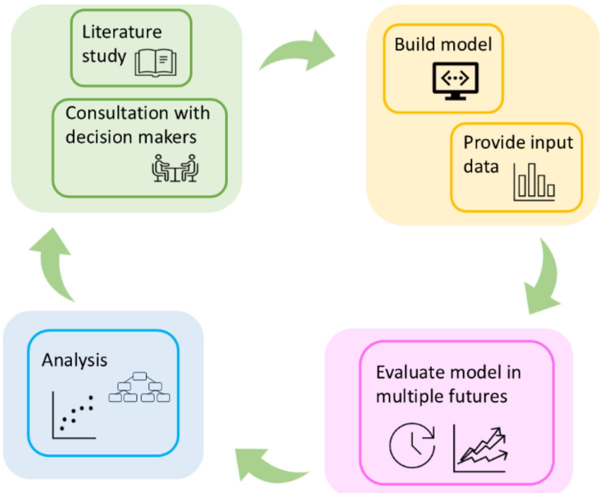


Figure 3. Overview of the RDM procedure as adapted in this study.

Part II: Literature review

5. Method – Narrative Grey Literature Analysis

As described in section 4. *Research Design*, the aim of this literature study is to get enhanced insight into the topic of CCU/S and factors that could affect an investment. Due to the limited study scope, the analysis does not claim to be extensive. Instead, the purpose is to gain a broad overview of the topic – which is why a narrative literature study is suitable (Leenaars et al. 2020). However, as pointed out by Leenaars et al., there is a significant risk of bias when performing a narrative review. They even dissuade students or others new to a field from performing narrative reviews because of the risk of selection bias (Leenaars et al. 2020). Nevertheless, with the scope given, it was not possible to perform a systematic review, making a narrative review an acceptable option.

Moreover, to get an up-to-date view on the topic, grey literature is deemed to be a valuable source as well, meaning that the material gathered is not exclusively from reviewed scientific publications, but also from reports and other material from e.g. companies and governments (Karolinska Institutet 2023). However, in lack of the peer-reviewing process of scientific publications, it should be noted that grey literature might be of varying reliability (Karolinska Institutet, 2023).

In summary, the study will be of the narrative type, including grey literature. The review starts with a general description of CCS and CCU as technologies, followed by an account of uncertainties related to CCS and CCU.

6. Technology and System Descriptions

6.1 Principles of Carbon Capture

Carbon Capture (CC) technology has three main capturing routes: pre-combustion, post-combustion, and oxyfuel-combustion (Fagerström & Nyberg 2022), although there are also other technologies like direct air capture (SEA 2023b). The post-combustion route means that CO_2 is captured from the flue gas of a combustion process and is the simplest route when retrofitting carbon capture to an existing power plant (Fagerström & Nyberg 2022). Examples of post-combustion routes are MEA (Monoethanolamine) and HPC (Hot Potassium Carbonate) (Beiron, Normann & Johnsson 2023). In both routes, the flue gas enters an absorber column where CO_2 is absorbed by the solvent MEA or HPC, respectively. The solvent and CO_2 are then separated in a stripper column, and the CO_2 is compressed and liquefied (Beiron et al. 2023).

One main difference between the methods is that MEA is heat-driven and HPC electricity-driven (Beiron et al. 2023). Hence, when performing a carbon capture retrofit, the choice of capturing technique impacts heat and electricity production. For instance, Beiron et al. compared the impact of installing MEA and HPC at a combined heat and power plant in Västerås and concluded that MEA mainly reduces heat output and HPC mainly reduces electricity output (Beiron et al. 2023). However, these effects could be partly compensated by instalment of a heat pump to recover heat from the carbon capture process (Beiron et al. 2023). After the CO_2 has been separated, it is either transported to a storage site, used directly e.g. in a greenhouse, or used for the production of some other product.

6.2 Principles of CCS

When permanently storing CO_2, there are several possible pathways. The transport could either be done through pipes, train, or truck, with a number of interim storage and CO_2 compression and liquefication steps along the way (SEA 2023c). There are also several possible storage types. In the Swedish Energy Agency's report *"Ett skepp kommer lastat", it* *is stated that aquifers in the Nordic Sea are* the most reasonable alternative for Swedish CCS (SEA 2023c).

6.3 Principles of CCU

In contrast to CCS, Carbon Capture and Utilization (CCU) means that the captured carbon is in some way utilised. There are several possible areas of use, including the incorporation of CO2 into building materials, the synthesis of polymers or chemicals, direct use (e.g. in food production), and conversion into fuel (Mertens et al. 2023). Since this study is restricted to the production of electronic sustainable aviation fuel, this will be briefly elaborated upon.

6.4 eSAF

In 2019, the aviation industry was responsible for 13.9% of CO_2 emissions from EU transport (European Commission n.d. c). Although powering aircrafts electrically would be the most energy-efficient solution to reduce these emissions, current battery technology is not mature enough to completely replace liquid fuels any time soon (Abid, Ridjan Skov, Vad Mathiesen & Alberg Østergaard 2025). In the EU, attention has instead been given to so-called sustainable aviation fuels (SAFs). Most notably, in October 2023, the EU introduced *Regulation (EU) 2023/2405 of the European Parliament and of the Council of 18 October 2023 on ensuring a level playing field for sustainable air transport* (ReFuelEU Aviation) – a SAF blending mandate to push the use of SAF in the EU.

SAF can either be bio-based or produced from electricity, in which case it is called electronic SAF (eSAF). The production of eSAF (also referred to as power-to-liquid fuel or e-kerosene) starts with hydrogen (H_2) production via water electrolysis. The H_2 is then reacted with CO_2 through a methanol-based or Fischer-Tropsch (FT) based process (Abid et al. 2025), the latter one being the most mature technology for e-fuel synthesis (Gebellí Carrasco & Melander 2023). For the FT-process, H_2 and CO_2 are reacted to form syngas, which in turn is converted into syncrude (Seymour, Held, Stolz, Georges & Boulouchos 2024). This mixture of fuel products is then separated into eSAF, e-diesel, and e-naphtha and/or e-gasoline (Seymour et al. 2024). The procedure is summarized in Figure 4 (Meurer & Kern 2021).

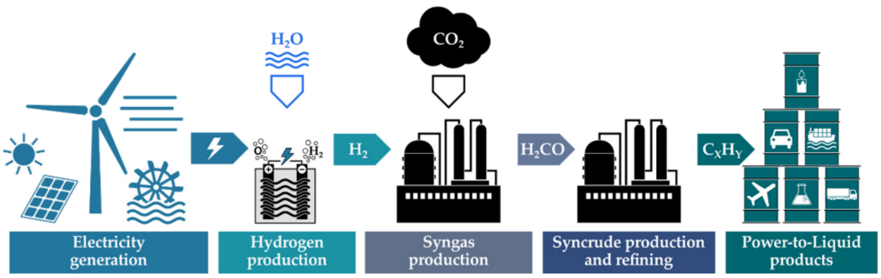


Figure 4. Overview of production pathway for electronic sustainable aviation fuel (eSAF.). Illustration by (Meurer & Kern 2021), from "Fischer–Tropsch Synthesis as the Key for Decentralized Sustainable Kerosene Production", licensed under CC BY 4.0.

7. Uncertainties

As presented in section 6. *Technology and system descriptions*, both CCS and CCU are compromised by several subsystems, each with their own expenses. However, there are potential economic advantages with CCU/S technologies like revenue from selling eSAF and CRCs, funding, and avoided emission fees. The cashflows of CCS and CCU systems are compromised by many parameters, many of which come with uncertainties. In the following, a selection of uncertainties related to the economics of a CCU/S investment will be elaborated upon. To give an overview of the uncertainties discussed, they are illustrated in Figure 5.

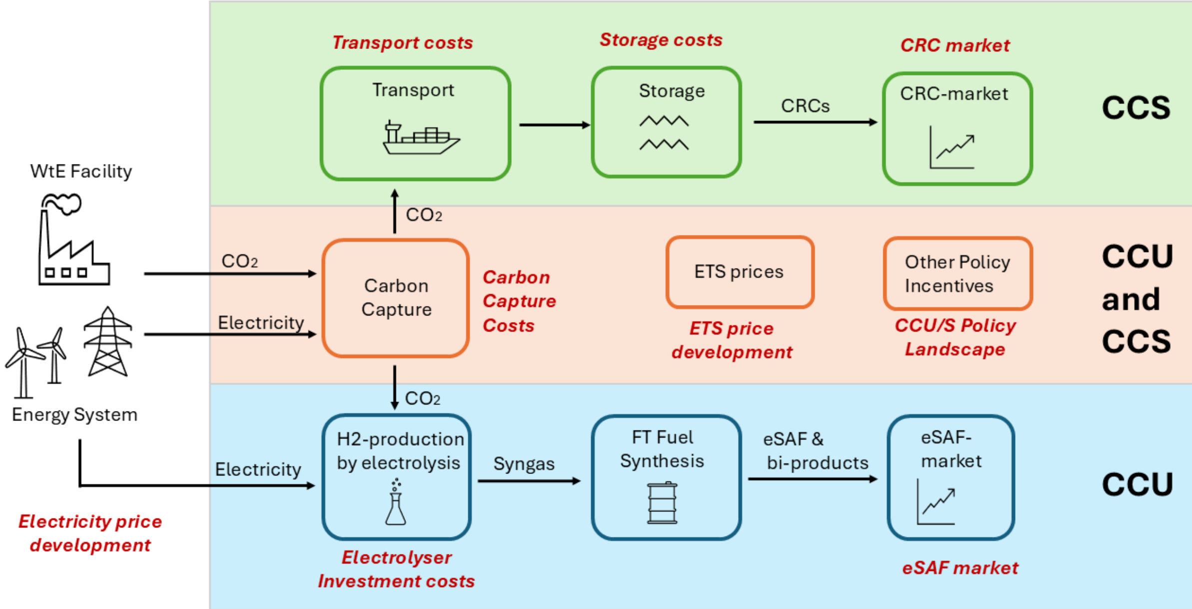


Figure 5. Simplified overview of the CCS and CCU system, where the uncertainties discussed in the literature review are marked in red.

7.1 Uncertainties Related to Carbon Capture Facility Costs

CCU/S technologies are capital-intensive, one reason being the high costs related to carbon capture technology. For CCS, it could account for as much as 70-80% of the total costs (Dubey & Arora 2022). The carbon capture costs could vary depending on the plant's design, size, and efficiency (Kourosh Mahjour & Faroughi 2023) as well as unforeseen events in construction or operation. However, the cost of carbon capture is expected to decrease as more CCS facilities are installed (Kourosh Mahjour & Faroughi 2023).

7.2 Uncertainties Related to Electrolyser Investment Costs

In the production of eSAF, the price of the electrolyser often dominates the capital costs (Gebellí Carrasco & Melander 2023). There are three main types of electrolysers: Alkaline Electrolysis Cell (AEC), Proton Exchange Membrane Electrolysis Cell (PEMEC), and Solid Oxide Electrolysis Cell (SOEC) (Danish Energy Agency, 2025b) out of which this study focuses on AEC electrolysers. Figure 6 shows price predictions applicable to this type of electrolyser as provided by two reports: one by the Danish Energy Agency (2025a) and one by Remko Detz and Marcel Weeda (2022) at The Netherlands Organisation for Applied Scientific Research (TNO). The prices have been converted to SEK(2025) per installed MW (MWe). Although there is a trend of decreasing costs with time, there is a clear spread.

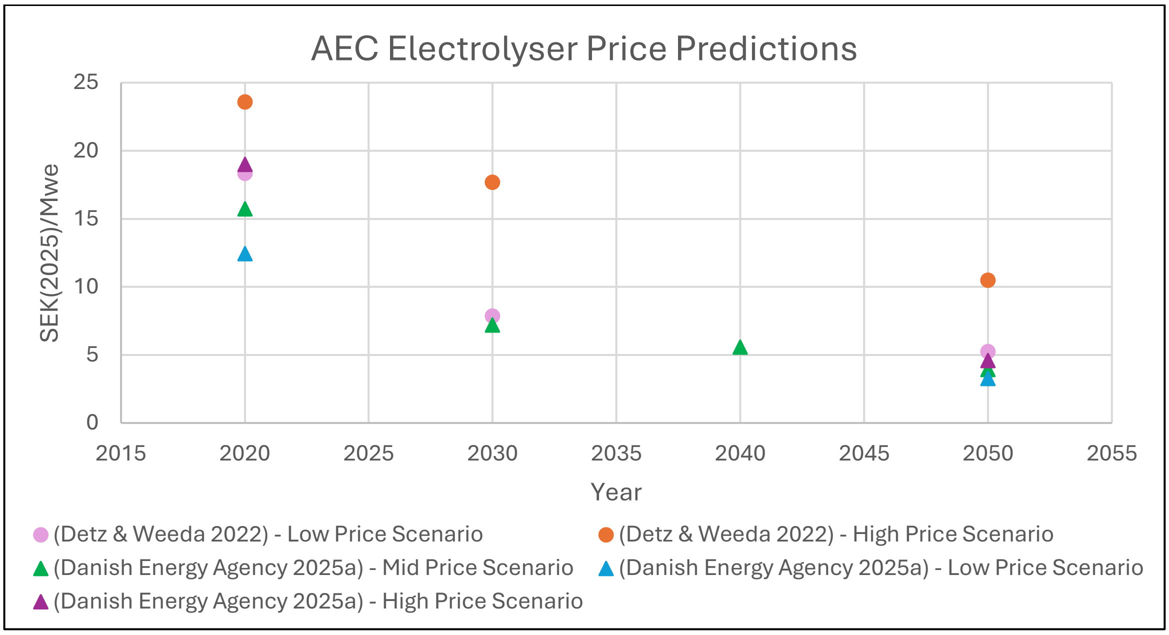


Figure 6. Predicted electrolyser prices between 2020 and 2025. The price has been converted to SEK(2025) per installed MW (MWe). (Detz & Weeda 2022; Danish Energy Agency 2025a)

7.3 Uncertainty in Transport and Storage Costs

The costs of CO_2 transport and storage could vary greatly. Not only do they depend on the CC-plant's size and location, but as Fagerström and Nyberg (2022) point out, a CCS-investor is also faced with many strategic choices: where to store the CO_2, how to transport it there, where to locate intermediate storage sites, and how to scale these. With different strategies also come various uncertainties – e.g. costs of pipes or truck fuel. Moreover, transport and storage could potentially become cheaper if more CCS projects are finalised and CCS infrastructure is developed (Smith et al. 2021). For instance, one source mentions the possibility of a Swedish transport hub being built in the future – something that could decrease transport costs (SEA, 2023c). On the other hand, a scale-up of CCS could also mean uncertainty regarding meeting storage and transport demand. For instance, ship transport from Sweden could become a limiting factor in Swedish CCS infrastructure (SEA, 2023c). However, no sources have been found discussing or predicting how this could affect transport and storage costs.

7.4 Uncertainties in ETS and Electricity Prices

7.4.1 ETS-prices

The EU Emissions Trading Scheme (ETS) is a cap-and-trade system for CO_2 emissions where operators who are part of the system must pay for all or a fraction of their emissions (European Commission, n.d. b). Swedish WtE plants are part of this system and pay for all their fossil emissions (SEA, 2023b). Thus, there is an important difference between CCS and CCU investments: a CCS installation means that the emission costs of the stored CO_2 are avoided, whereas for CCU, all emission costs remain. Today, the emission fee is too low to alone incentivise a CCS investment (Fagerström & Nyberg 2022). Moreover, since the price depends on both EU policies, market forces, and geopolitics, it is difficult to predict its development (Lamberts-Van Assche et al. 2023), making the profitability of CCS and CCU uncertain. In fact, CO_2 costs have been recognised as the greatest uncertainty of both technologies (Boongaling Agaton 2021; Lamberts-Van Assche & Compernolle 2022b).

7.4.2 Electricity Prices

Both CCS and CCU projects are affected by electricity prices. The carbon capture technique itself is energy demanding and if installed at a WtE plant, it will reduce the plant's electricity production (Bisinella, Nedenskov, Riber, Hulgaard & Christensen 2022), causing a decrease in revenue. For eSAF production, electricity costs are described as a main cost driver due to the large amounts of electricity consumed in electrolysis (Seymour et al. 2024). At the same time, today's energy prices are volatile (Lee et al. 2023) and their development depends on many factors, which make them hard to predict. This causes deep uncertainty regarding CCU/S's electricity costs.

7.4.3 Scenario-Based Modelling of ETS and Electricity Prices

There are many studies that predict ETS and electricity costs. Among them, Bisaillon, M., Johnsson, J., Löfblad, E., Rensfeldt, A., Sahlin, J., and Unger, T. from the consulting company Profu have developed scenarios from which they have predicted the development of ETS and electricity prices. The three scenarios are Cost-Conscious Transition (CCT), Energy Security First (ESF), and Renewable Sustainability First (RSF) (Profu, personal communication [p.c.] 2024). The European Commission has also developed two scenarios, With Existing Measures (WEM) and With Additional Measures (WAM), which predict the ETS-price development from 2030 to 2050 (SEA 2025b). Based on this, the Swedish Energy Agency has predicted the ETS price in 2060 (SEA 2025b). The scenarios mentioned are described in

Table 2, and the ETS price predictions, as well as historic ETS prices, are presented in Figure 7.

Table 2. Descriptions of the scenarios as developed by Profu and the European Commission (Profu, p.c. 2024; SEA 2025b)

Source	Scenario	Description
(Profu, p.c. 2024)	Renewable Sustainability First (RSF)	The EU prioritises meeting its climate goals.
	Energy Security First (ESF)	The EU works towards the climate goals but mainly prioritises energy independence.
	Cost-Conscious Transition (CCT)	The effort for a green transition stagnates, and the EU focuses on its economy.
(SEA 2025b)	With Existing Measures (WEM)	The ETS prices follow the European Commission's recommendations, based on current politics.
	With Additional Measures (WAM)	Additional political measures are taken, causing ETS prices to reach even higher values.

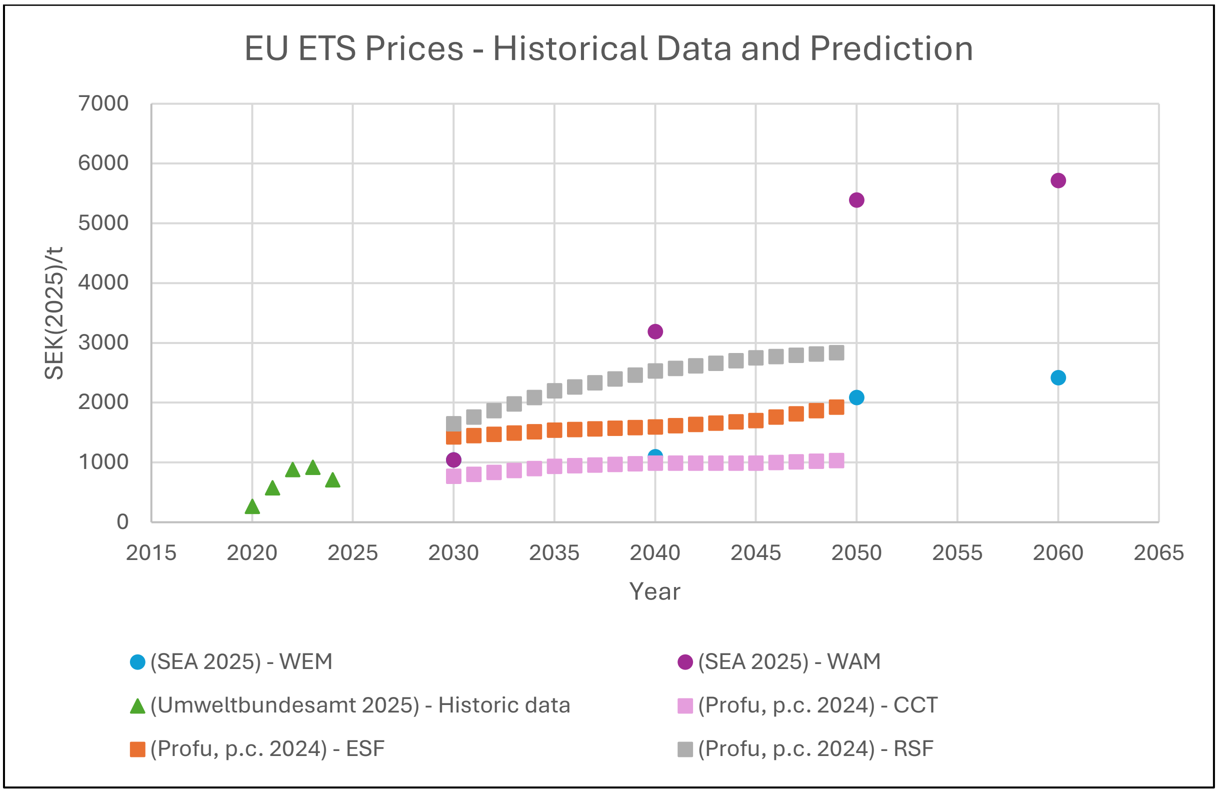


Figure 7. Past and predicted development of EU ETS emission fees. Values have been converted to SEK(2025)/t. Historic data from (Umweltbundesamt 2025). Predictions presented by (Profu, p.c. 2024) and (SEA 2025b)

As for electricity prices, (Profu p.c. 2024) has for each of their scenarios CCT, ESF, and RSF predicted the price trajectory in the electricity area SE3 (which is the electricity area where Gärstadverken is located). These are presented in Figure 8. According to their prediction, the electricity prices converge over time and stabilise around 2040. However, this prediction does not include variations due to weather or changes in the state of the market (Profu, p.c. 2024).

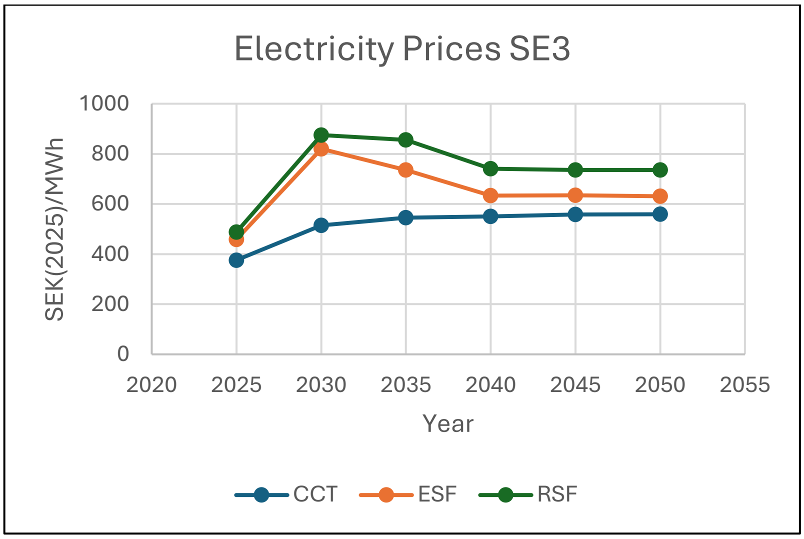


Figure 8. Electricity price predictions in the scenarios CCT, ESF, and RSF (Profu, p.c. 2024). Values have been converted to SEK(2025)/MWh.

7.5 The CRC Market

One potential revenue for CCS projects is selling carbon credits gained from storing biogenic CO_2. According to Avfall Sverige, two types of markets could become relevant: a voluntary carbon market (VCM) and a compliance market stimulated by laws and regulations (Hansen & Jensen 2023). The VCM market consists of companies or individuals buying CRCs to compensate for their carbon-emitting activities (Fagerström & Nyberg 2022). For example, in May 2023, Microsoft closed a deal with Stockholm Exergi on 3.3 million CRCs in a ten-year period (Stockholm Exergi 2024). In 2023, the average price for carbon credits from BECCS was at 300 USD/t CO_2 (Smith et al. 2024). Nonetheless, it is a fragmented market with large variation in credit prices (Michaelowa et al. 2023) whose development shows both non-linearity and instability (Zheng, Li, Yue & Zhang 2024). Thus, it is difficult to estimate the CRC demand and price development, making the CRC price deeply uncertain.

Another way to gain profit from CRCs would be through compliance markets. The EU ETS, the EU Effort Sharing Regulation (ESR), and Article 6 in the Paris climate agreement could be potential creators of compliance markets where the demand in CRCs could be boosted (Hansen & Jensen 2023). For instance, integrating CRCs in the EU-ETS could result in carbon credits and emission allowances having similar prices (Stenström et al. 2023). Nevertheless, today it is not possible to sell CRCs within any of these markets. Although the conditions for CRC trading are being developed (Hansen & Jensen 2023), there is still uncertainty regarding what CCS-investors could expect in revenue.

7.6 The eSAF Market

Currently, there is no established eSAF market. One main hurdle for eSAF is its high production cost compared to both conventional aviation fuels, such as kerosene, as well as biobased SAFs. This can be seen from Figure 9, which includes the 2024 price of synthetic and bio-based aviation fuels, either as a market price or an estimation for fuels with no established market. The data and estimations are provided by the European Union Aviation Safety Agency (EASA) in the briefing note *2024 Aviation Fuels Reference Prices for ReFuelEU Aviation* from 2025.

However, it is possible that the eSAF production cost could decrease over time, for example due to improvements in energy- and H_2-production efficiency. Various sources have predicted the production price of eSAF and how it could develop, a selection being presented in Figure 10. (It should be noted that out of the sources included in Figure 10, only (Transport & Environment [T&E] 2024) explicitly state that their price estimations include a profit margin.) As can be seen from the figure, the price development is also uncertain, and none of the sources expect the eSAF price to decrease below the 2024 price of conventional aviation fuels. According to an insights report from Project Skypower, the business case of eSAF will have to be created through political measures, not economics (Project Skypower 2024).

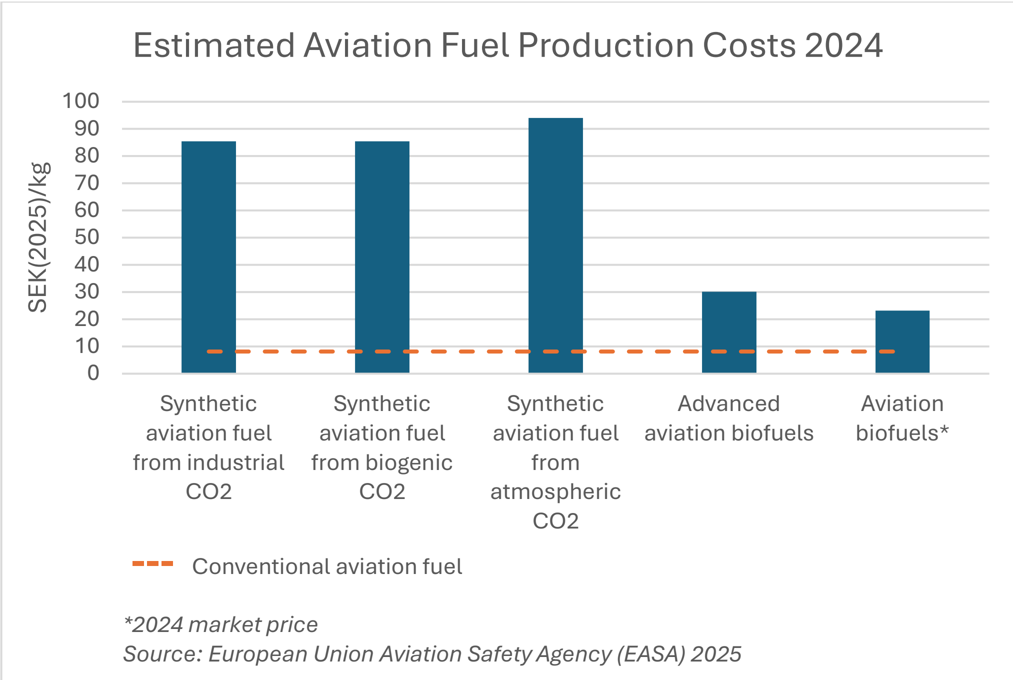


Figure 9. The estimated production costs 2024 of synthetic and biobased fuels included under the EU regulation ReFuelEU Aviation. The production costs have been converted from €/t to SEK(2025)/kg. The estimations exclude profit margin. Data: (EASA 2025).

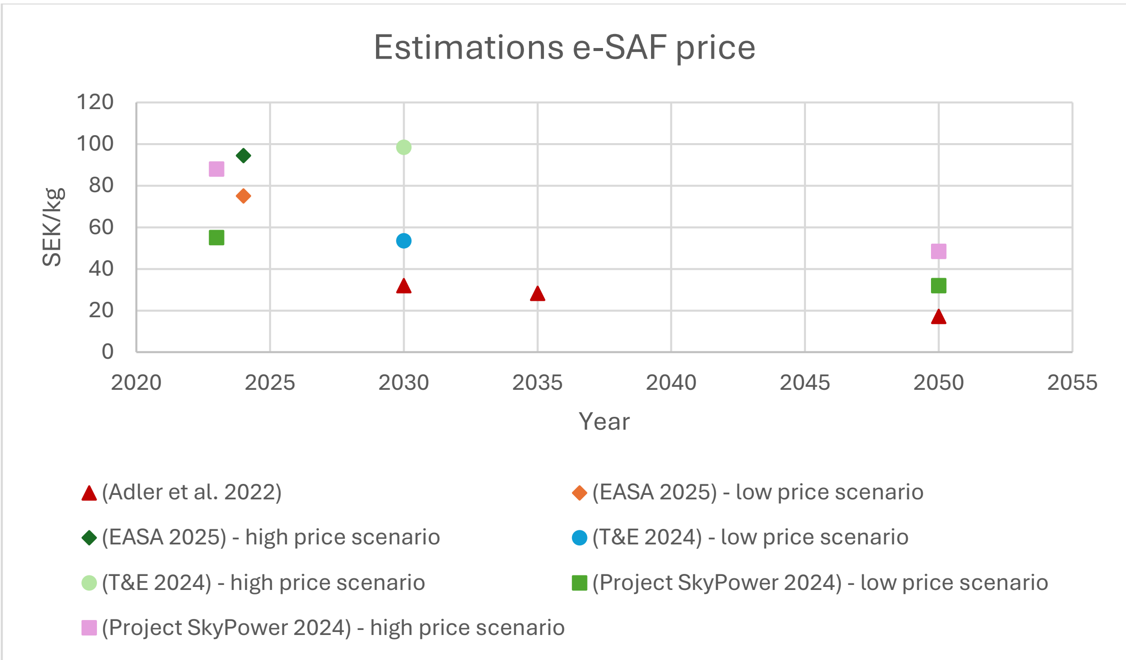


Figure 10. Estimations of future eSAF prices. The values have been converted to SEK(2025)/kg. Data: (Adler, Boonekamp & Konijn 2022; EASA 2025; T&E 2024; Project Skypower 2024)

As earlier mentioned, one policy promoting eSAF is the EU regulation *Regulation (EU) 2023/2405 of the European Parliament and of the Council of 18 October 2023 on ensuring a level playing field for sustainable air transport* (ReFuelEU Aviation). This regulation states that from 2030, fuel supplied at EU airports must contain at least 1.2% synthetic aviation fuel such as eSAF. The fraction will increase annually up to 35% by 2050 (ReFuelEU Aviation 2023) as illustrated in Figure 11. According to (Grimme 2023), this means that the annual eSAF production in 2050 would have to be approximately 13 million tonnes. Nonetheless, this provides that there are enough incentives for buying eSAF. As one measure, ReFuelEU Aviation states that each EU member state should introduce a financial penalty for aircraft operators not following the blending mandate. At a minimum, an aircraft operator not using enough synthetic SAF in their aircrafts should pay for the non-tanked fuel at a price of double the average cost of synthetic SAF (ReFuelEU Aviation 2023, article 12). This could secure the demand.

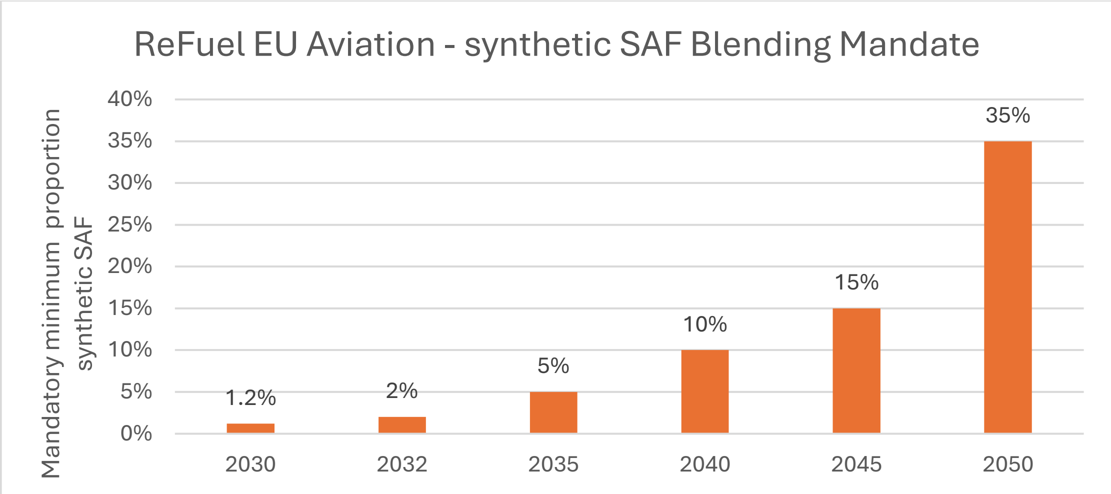


Figure 11. Diagram illustrating the synthetic SAF blending mandate of the EU regulation ReFuelEU Aviation (2023).

Another market uncertainty is the availability and price of eSAF made by other producers. For instance, the conditions for eSAF production in the US are deemed more favourable, possibly competing with fuels produced in Europe (Project Skypower 2024). On the other hand, it is also stated that the rising eSAF demand, followed by the blending mandate, will be difficult to meet at all (Project Skypower 2024). Again, this of course provides that the policy incentives set in the EU are long-term. This is one of the conditions lifted in an insights report from Project SkyPower, where actors from trade and industry highlight the need for ”(A) regulatory certainty on the e-SAF mandates, (B) adequate public funding via existing industry-generated tax or carbon pricing revenues (e.g. via the ETS) (C) long-term offtake agreements, and (D) appropriate de-risking measures to reduce first-of-a-kind project risk.” (Project SkyPower 2024, p. 7).

7.7 Policy Landscapes

Several studies highlight the need for more and long-term political support of CCU/S investments (Fagerström & Nyberg 2022; Kourosh Mahjour & Faroughi 2023; Lee et al. 2023). However, as stated by the Swedish Energy Agency, too high incentives in carbon capture technologies might result in fewer measures being taken to reduce fossil emissions and plastic waste. As a result, shaping the policies is a complex issue (SEA 2023a). Table 3 is a non-exhaustive summary of policies relevant to CCU/S investments in Sweden. As seen from the table, there are policies that could aid a CCU/S investment. Still, there is uncertainty regarding when and how much financial support can be received.

Table 3. Non-exhaustive summary of policies relevant to CCU/S investments in Sweden.

Policy	Description
Industrial Leap	A funding scheme available to projects that run until 2031 and aim at reducing greenhouse gas emissions, producing negative emissions, or supporting Sweden's net zero emission target. The fund is managed by The Swedish Energy Agency and consisted of 1 345 MSEK in 2025 (SEA 2025d). Funding has been given to projects related to CCS and CCU (SEA n.d.).
Climate leap	A funding scheme managed by the Swedish Environmental Protection Agency. One of the areas that can receive funding is the production of electro-fuels. However, only fuels produced using renewable electricity and biogenic CO_2 can be granted funding. (Swedish Environmental Protection Agency 2025a)
EU innovation fund	A fund that comprises revenues from the EU ETS system. Both CCS and CCU projects can be granted funding. (European Commission n.d. d)
Reversed auctions	Between 2026 and 2046, 36 BSEK are to be distributed to Swedish companies investing in BECCS. This is done through reversed auctions, where the actor which can capture and store biogenic CO_2 at the lowest price is granted financial support (SEA 2025c). Stockholm Exergi was granted roughly 20 BSEK in the first auction, and more auctions are to be held (SEA 2025a). However, it is also pointed out that the auctions might disfavour WtE plants (which emit both biogenic and fossil CO_2) since support only concerns capture and storage of biogenic CO_2 (Fagerström & Nyberg 2022)
Producer's responsibility of plastic	As a policy instrument to reduce plastic waste while supporting CCS and CCU investments, the Swedish Energy Agency has proposed that a producer's responsibility of plastic should be investigated. Producers putting virgin fossil plastic on the market would be charged with a fee, which in turn would be used to finance carbon capture and other emission-reducing efforts. (SEA 2023a)

Part III: RDM Analysis - Method

In this part of the study, the method of the RDM analysis is presented, starting with descriptions of common tools used in RDM analysis, followed by an account of how this study implements the RDM framework, as well as further details about the built model.

To recall, the RDM procedure is an iterative process where the model development and analysis are performed multiple times. The procedure can also be divided into five main steps, as shown in Figure 12.

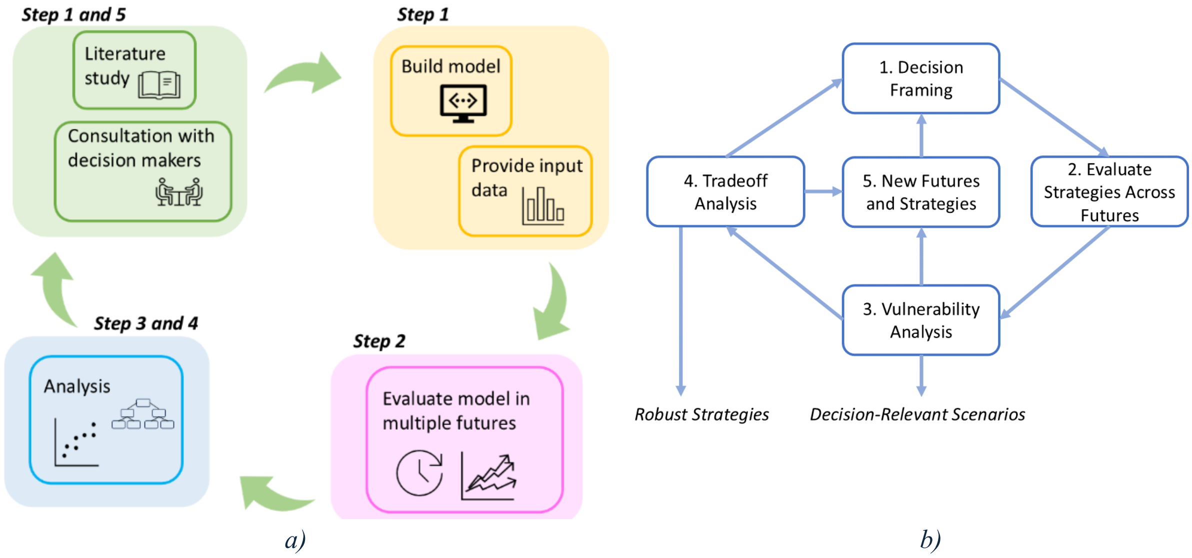


Figure 12. a) Overview of the RDM procedure as adapted in this study. b) The main steps of the Robust Decision Making (RDM) approach. Adapted by the author from a figure in Marchau et al. (2019), originally by Lempert et al. (2013).

8. Tools of RDM Analysis

As illustrated in Figure 12., the aim of RDM steps 3 and 4 is to search for vulnerabilities of strategies and trade-offs between them. In this section, tools that are commonly used to perform these steps are presented.

8.1 Scenario Discovery

Scenario discovery provides a means to investigate what conditions could cause a strategy to fail or succeed (Marchau et al. 2019). Scenarios could be described as sets of simulated futures where the values of one or more uncertainties have been restricted. Sets containing many futures where a decision fails/succeeds could then provide insights about what conditions make a strategy vulnerable.

Two metrics used to characterise scenarios are coverage and density (Lempert, Bryant & Bankes 2008). To give an example, consider the aim of finding the conditions resulting in $A > 0$. The case of interest is then "$A > 0$", and a scenario with high coverage would contain a large fraction of these cases. (If coverage is 1, all such futures are included in the scenario, and if 0, none are.) The density measures how many of the futures included in the scenario are cases of interest. (If the density is 1, the scenario only contains cases of interest, and if 0, none are included.) Hence, it is desirable to find scenarios with high coverage and high density as these could give valuable information about what conditions relate to success/failure (Lempert et al. 2008). Moreover, for the scenarios to be useful, they should be easy to interpret (Lempert et al. 2008).

8.1.1 CART

Classification and Regression Tree (CART) is a method to predict the value of a target variable (Krzywinski & Altman 2017). First, the user defines the case of interest in the form of a condition put on the target variable (e.g. the target variable is A and the case of interest is $A < 0$ which creates two classes: $A < 0$ and $A \geq 0$). The output data is then consecutively split into two subgroups according to conditions on the input parameters (such as $x1 < 5$). The CART algorithm tests different conditions on different input parameters to find the condition yielding the best split – i.e. the split where the subsets show maximum homogeneity with respect to the classes, and greatest heterogeneity between each other (Krzywinski & Altman 2017). The same procedure is then performed on each subset, generating a tree structure where each subgroup represents a scenario characterised by the earlier partitions. Figure 13 shows an illustrative example of a CART tree that predicts the conditions under which the target variable A is < 0 or ≥ 0. Conditions are put on the parameters x_1 and x_2.

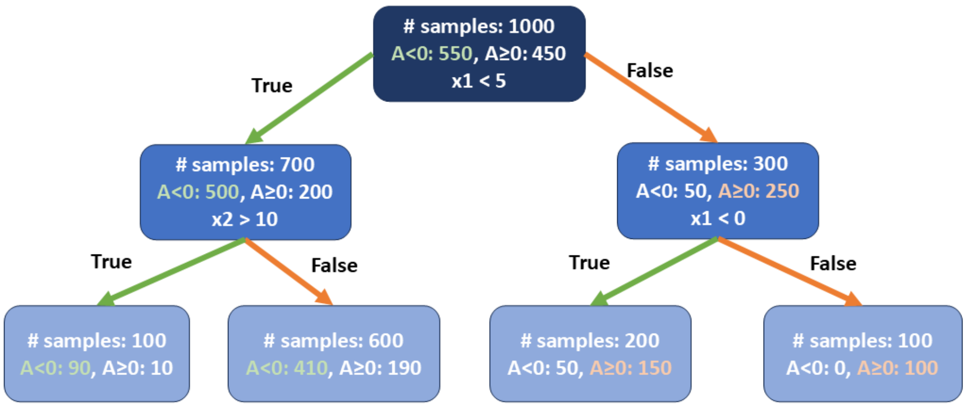


Figure 13. Illustrative example of a CART tree. The tree predicts the conditions under which the target variable A is < 0 or ≥ 0. Conditions are put on the parameters x_1 and x_2.

To measure homogeneity of the subsets, the concept of impurity is used – a metric that measures to what degree the classes in the subsets are mixed. One such metric is the Gini index. When the Gini index is zero, all data points in the subset belong to one class, and when it is 0.5, each class is equally represented (Krzywinski & Altman 2017). Apart from being used in the classification process, the Gini index could also be used to evaluate which factors were the most influential when creating the tree structure. The feature that contributes the most to impurity reduction is given the highest impurity importance (Nembrini, König & Wright 2018), also called feature score. Thus, parameters with high feature scores could be considered important predictors of which class the target variable belongs to.

The CART method is effective and generates trees that are intuitive to interpret (Krzywinski & Altman 2017) while able to capture complex, non-linear relationships in the data (Abellán-García 2022). On the other hand, the tree structure could be sensitive to changes in the data, especially if the subgroup that is to be split contains few samples (Berk 2008). This also increases the risk of overfitting, i.e. the algorithm responding to noise in the data (Berk 2008). Moreover, as more partitions are made, the result could become increasingly difficult to interpret.

One way to improve the performance of CART is pruning – methods to reduce overfitting and tree complexity. If pruning is performed before the tree is generated, it is called pre-pruning. Examples of pre-pruning strategies are 1. limiting the depth of the tree and 2. setting a minimum on the number of samples that can be further split into subgroups. (Esposito, Malerba, Semeraro & Kay 1997)

8.1.2 PRIM

The patient rule induction method (PRIM) is a so-called bump-hunting algorithm that aims to find regions in the output space with a high density and/or coverage of a given class. The regions are then presented in the form of conjunctive conditions on the input parameters, such as $100 \leq x1 < 200$ *and* $0 \leq x2 < 5$ (Nanning, Abu-Hanna & de Jonge 2008). It finds these subspaces in a process called "peeling" where the range of an input is decreased such that the outcome mean is maximized (Nanning et al. 2008). One peeling process results in a scenario, also called a box, with its own rules, coverage, and density (Bryant & Lempert 2010). The peeling procedure is illustrated in Figure 14 (Nassih & Berrado 2025).

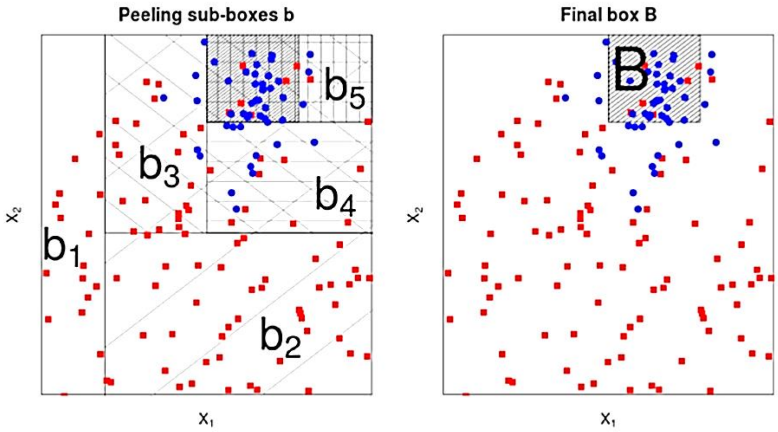


Figure 14. Example of peeling procedure performed by PRIM. The points belonging to the sought-after class are marked in blue, while X_1 and X_2 are the input parameters being peeled. Illustration by (Nassih & Berrado 2025), from "Breast Cancer Classification Using an Adapted Bump-Hunting Algorithm", licensed under CC BY 4.0.

PRIM is a widely used method in decision making involving deep uncertainties and produces interpretable scenarios (Shokri, Walker, van Dijk, Wright & Pauwels 2018). However, (Bryant & Lempert 2010) point out that when working with high-dimensional data showing low-dimensional shapes in the output, there is a risk that PRIM puts large constraints on an input that the output is not even sensitive to. To avoid such overfitting, one method they suggest is calculating the quasi-p (qp) values of the restricted inputs. Although the accuracy of qp-values is limited, comparing the qp-values of restricted parameters provides an indication on how sensitive the output is to each of them (Bryant & Lempert 2010). More specifically, a high qp-value indicates that the constraint put on the parameter might not be crucial for defining the scenario (Bryant & Lempert 2010).

8.2 Sobol Sensitivity Analysis

Sobol sensitivity analysis is a method to evaluate how the output variance of a model is affected by its inputs (Nossent, Elsen & Bauwens 2011). It quantifies this influence in the form of sensitivity indices (Nossent et al. 2011) where the first-order sensitivity index of an input X_i ($S_{1,i}$) describes the average contribution of X_i alone on the output variance, whereas the second-order sensitivity index $S_{2,ij}$ captures the effects of interactions between parameters

X_i and X_j. Lastly, the total-order sensitivity index $S_{T,i}$ describes the *total* contribution of X_i on the output variance – both the contribution from X_i alone and from interactions with the other inputs (Nossent et al. 2011).

Sobol sensitivity analysis is model independent (i.e. handles non-linear and non-monotonic models where factors interact) and has been described as accurate and reliable (Yang 2011). However, it is computationally intensive, especially in cases where many model evaluations are required for the sensitivity indices to converge (Nossent et al. 2011). Moreover, the inputs should be independent of one another (Wiederkehr 2018).

8.3 Trade-off Analysis

In RDM, one way of performing trade-off analysis is by investigating which decision is the most robust – i.e. which strategy performs adequately in many different futures (Marchau et al. 2019). There are several ways robustness can be measured. One example is the satisficing domain criterion where the performance of a strategy is compared to some performance requirement (Stenström et al. 2024). The strategy that has this criterion met in the most SOWs is the most robust (Stenström et al. 2024). Another metric is Salvage's criterion which states that a strategy is robust if it has the smallest maximum *Regret* (Marchau et al. 2019). *Regret* is further explained in section 9.1.2 *Performance Measurement*.

9. Steps of RDM

Figure 15 shows how the RDM steps shown in Figure 12. are realised and adapted to this study. In the following, the steps will be further described, but to summarise:

- **Step 1:** Based on discussions with decision-makers and results from the literature analysis, different investment cases are identified. For each case, the performance of the CCS(CCU) investment is evaluated by calculating its net present value and using this to quantify the Regret of investing in CCS(CCU) rather than not investing. To calculate these metrics, the CCS's (CCU's) cashflows, as well as the uncertainties related to them, are modelled. All modelling and subsequent analysis is performed in the open-source Python library Rhodium (Hadjimichael, Gold, Hadka & Reed 2020).
- **Step 2:** The uncertainties in the model create an input space from which States of the World (SOWs) can be sampled. For each identified investment case, the performance metrics are evaluated in 10 000 sampled futures.
- **Steps 3 and 4:** The evaluated performance metrics are visualised and analysed using plots, Sobol sensitivity analysis, and the scenario discovery methods CART and PRIM.
- **Step 5:** The results from the analysis are used to iterate on the model – for instance, by reformulating cashflows and finding new uncertainties and cases to investigate.

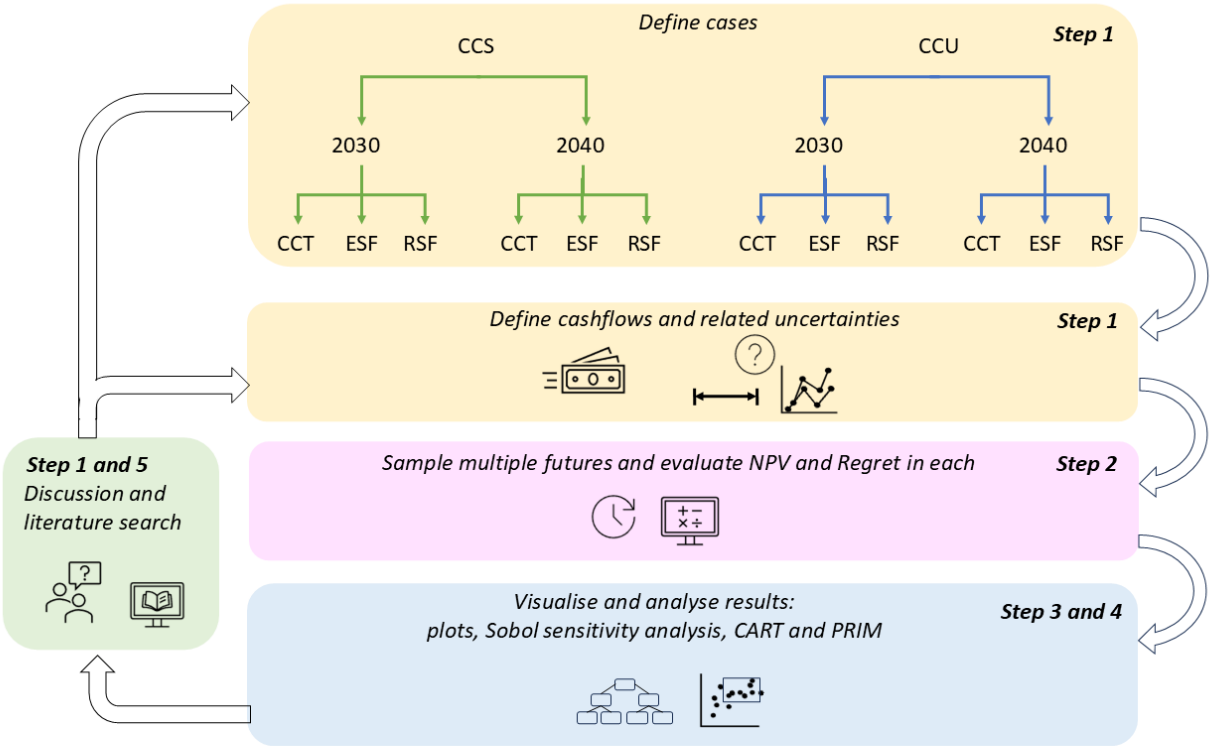


Figure 15. Illustration of how the main steps of RDM were realised and adapted to this study.

9.1 Step 1: Decision Framing - Building the Model

As highlighted by the RDM framework, the decision-makers should be involved in the decision framing step. As such, meetings with representatives at TvAB were held weekly, during which the problem framing, system boundaries, and uncertainties were discussed. Information and insights from these meetings were complemented by results from the literature study (see Part II: *Literature Review*) to iterate on the model and identify a system boundary.

9.1.1 System Boundary

Figure 16 shows the system boundary of the study. A couple of things can be noted. Firstly, how the operations of Gärstadverken (e.g. the heat and electricity output) are affected by a carbon capture installation is not included. The capacity of the energy system is also excluded – instead, it is assumed that the electricity demand can always be met. The fuel market, as well as potential incomes from negative emissions, are also not included explicitly. The reason for this is further described in section 10.1 *NPV Calculations*. The same goes for funding, where no funding amounts are investigated explicitly. Other policy incentives, such as lowered electricity taxes for CCS or those unknown to the author, are also outside the system boundary. Lastly, any efficiency drop or other effects of an aging system are neglected.

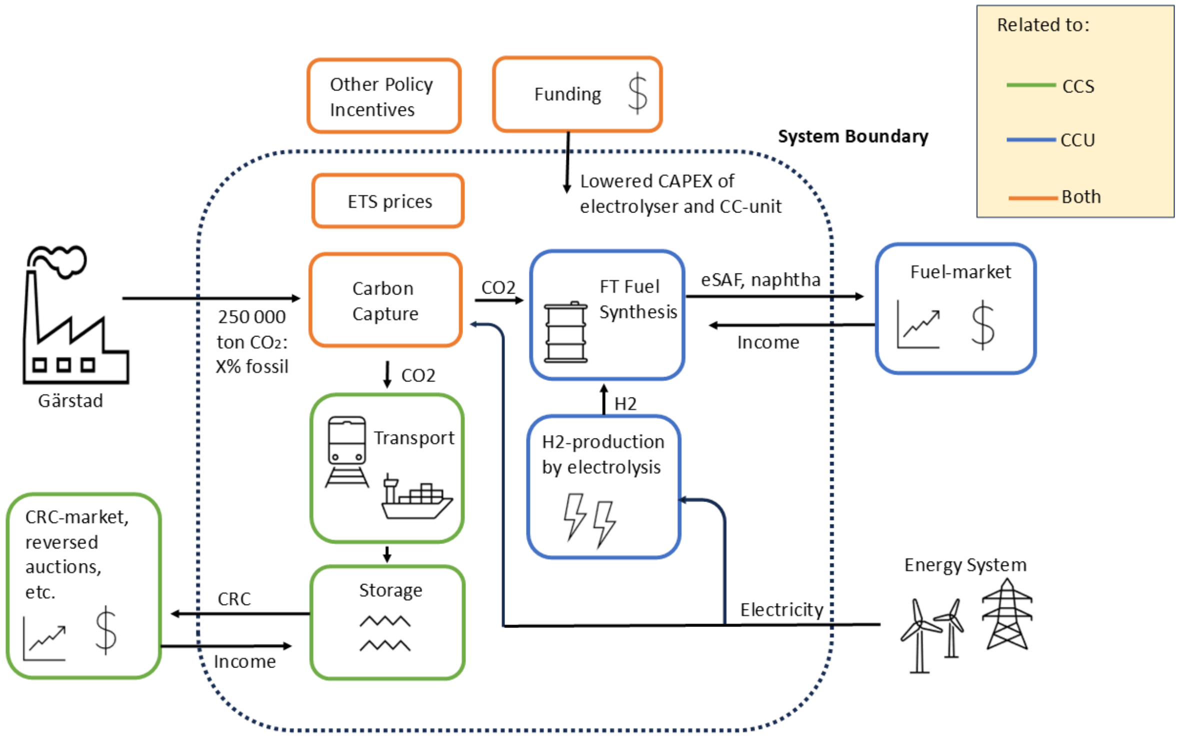


Figure 16. System boundary of the RDM analysis.

9.1.2 Performance Measurement

Like (Stenström et al. 2023), this study applies the net present value method to evaluate CCU/S investment strategies. Net present value (NPV) is a widely used method to evaluate investment decisions whilst considering the time value of money (Arnaboldi, Azzone & Giorgino 2015). This is done by summing future cashflows which are converted into today's value via a discount rate. More specifically:

$$NPV = \sum_{t=t_{inv}}^{T} \frac{Incomes - Costs}{(1 + DR)^t}$$

where t_{inv} is investment year, T is the useful lifetime, and DR the discount rate. When comparing investment decisions, the decision generating the highest NPV is preferable (Arnaboldi et al. 2015).

Another performance metric applied in this study is Regret. This metric quantifies how a strategy performs in a future scenario in comparison to either: 1. the best solution in that scenario or 2. a baseline performance in that scenario (Marchau et al. 2019). As there is no baseline performance in this study, the first definition is used. The CCU/S investments are compared to not investing at all, meaning that the Regret of investing in CCS (R_{CCS}) or CCU (R_{CCU}) is calculated as:

$$R_{CCS} = \max(NPV_{CCS}, NPV_{n.i.}) - NPV_{CCS}$$

$$R_{CCU} = \max(NPV_{CCU}, NPV_{n.i.}) - NPV_{CCU}$$

where NPV_{CCS}, NPV_{CCU} and $NPV_{n.i.}$ is the NPV of investing in CCS, CCU or not investing respectively. Details about the final NPV calculations, such as included cashflows and input values, are presented in section 10. *Model building*.

9.1.3 Examined Uncertainties

As described earlier, there are multiple uncertainties related to the cashflows of CCU/S projects. However, due to the limited study scope, only a selection of uncertainties is investigated. This selection was continuously updated as the model was built, and insights were gained during meetings at TvAB. Table 4 shows the final selection. Referring back to section 1.4.1 *DMDU*, deep uncertainty in a parameter arises when there are many plausible futures, when the future is unknown, or when there are several alternative models for describing the parameter. As shown in the literature analysis, the factors listed in Table 4 all come with great uncertainty while being considered important factors for the economics of CCU/S. How the uncertainties are modelled and what range of values they are given is presented in section 10. *Model Building*.

Table 4. Uncertainties that are included in the RDM analysis.

Applies to	Uncertain factor
CCS and CCU	*Electricity prices*
	ETS prices
	Capital expenses of the carbon capture unit
	The amount of captured CO_2 that is fossil
CCS	*Price of CRCs*
	Transport and storage costs
CCU	*Development of capital expenses of the electrolyser*
	Price e-SAF is sold for

9.1.4 Investigated Cases

In the final model version, there are 12 investigated cases. First, there are two separate analyses analysing the Regrets R_{CCS} and R_{CCU} respectively. The investment years 2030 and 2040 are also examined separately, resulting in four different strategies:

- Investing in CCS 2030
- Investing in CCS 2040
- Investing in CCU 2030
- Investing in CCU 2040

To capture the relationship between electricity and ETS prices, the scenario formulations Cost-Conscious Transition (CCT), Energy Security First (ESF), and Renewable Energy First (RSF), as identified by (Profu p.c. 2024), are utilised to develop three different trends in ETS and electricity prices. (For descriptions of the scenarios, see Table 2 in section 7.4.3 Scenario-Based *Modelling of ETS and Electricity Prices*.) These ETS and electricity trends are described in section 10.2.2 *Modelling of Uncertainties*. The four strategies applied to the trends results in 12 different cases, as illustrated in Figure 17.

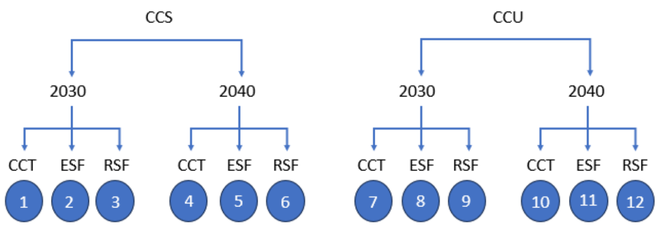


Figure 17. Illustration of the 12 cases investigated separately in the RDM analysis.

To build the system model and perform the rest of the RDM analyses, the open-source Python library Rhodium is used. Rhodium is specifically made for various types of robustness analyses and exploratory modelling, RDM included (Hadjimichael, Gold, Hadka & Reed 2020).

9.1.5 XLRM-table

Summaries of the CCS and CCU analyses are presented in the XLRM-tables labelled Table 5 and Table 6 respectively. In each case, ETS and electricity prices are specific to the scenarios CCT, ESF, and RSF.

*Table 5. The XLRM table of the RDM analysis regarding the decision investing in CCS or not investing. Uncertainties marked * are specific to the scenarios CCT, ESF, and RSF.*

CCS	
Uncertain Factors (X)	**Policy Levers (L)**
- *Price of CRCs* - *Transport and storage costs* - *Electricity prices** - *ETS prices** - *CAPEX carbon capture unit* - *Percentage of captured CO_2 that is fossil*	- *Investing in CCS 2030 or 2040* - *Not investing*
Relationships (R)	**Performance Metrics (M)**
- *Modelling in Rhodium*	- *Net present value* - *Regret*

*Table 6. The XLRM table of the RDM analysis regarding the decision investing in CCU or not investing. Uncertainties marked * are specific to the scenarios CCT, ESF, and RSF.*

CCU	
Uncertain Factors (X)	**Policy Levers (L)**
- *Price eSAF is sold for* - *Electricity prices** - *ETS prices** - *CAPEX carbon capture unit* - *Percentage of captured CO_2 that is fossil* - *Development of electrolyser CAPEX*	- *Investing in CCU 2030 or 2040* - *Not investing*
Relationships (R)	**Performance Metrics (M)**
- *Modelling in Rhodium*	- *Net present value* - *Regret*

9.2 Step 2: Evaluating Strategies Across Futures

Having defined performance metrics, cashflows, as well as cases and uncertainties to investigate, the next step of the RDM analysis is to evaluate the investment strategies across multiple futures. In accordance with the RDM framework, all uncertain parameters are given a uniform distribution, which in turn creates an input space. Then, for each investment year (2030 and 2040) and scenario (RSF, ESF, and CCT), 10 000 futures are sampled using Rhodium's Latin Hypercube Sampling (LHS) – a sampling method which, according to (Bryant & Lempert 2010), is suitable for scenario discovery. For each future, the net present values NPV_{CCS}, NPV_{CCU}, NPV_{wait} as well as the Regrets R_{CCS}, R_{CCU} are calculated.

9.3 Step 3 and 4: Vulnerability and trade-off analysis

To identify vulnerabilities and trade-offs, the results are visualised and analysed using scatter plots, Sobol sensitivity analysis, and the scenario discovery algorithms Patient Rule Induction Method (PRIM) and Classification and Regression Tree (CART) – all of which are available analysis tools in Rhodium. How the analyses are performed is described below. Moreover, although the RDM workflow includes investigating the robustness of different strategies to identify trade-offs, this study refrains from doing so. The reasons why are also presented in the following.

9.3.1 CART

For all CCS cases, the target variable is R_{CCS}, and the examined condition is $R_{CCS} = 0$. For CCU cases, the target variable is R_{CCU}, and the examined condition is $R_{CCU} = 0$. Rhodium uses the CART algorithm provided in the SciKit toolkit – a kit which also includes tools to evaluate the feature scores and classification accuracy of decision trees. When calculating the accuracy score, the 10 000 simulated futures are divided into a train and test set consisting of 7000 and 3000 futures respectively. Then, to reduce the tree complexity whilst avoiding under-fitting, pre-pruning is performed with the aim of finding the simplest tree possible while keeping the accuracy above 85%. The final trees were at most four stages deep and had at least 100 samples in each subgroup.

9.3.2 PRIM

Same as in CART, the classifications $R_{CCS} = 0$ and $R_{CCU} = 0$ were examined. As PRIM produces many boxes of varying density and coverage, it was chosen only to investigate boxes with a density of ~90%. Although it might decrease the coverage, this restriction would ensure that the rules mainly apply to the case of interest. Moreover, with no built-in tool to measure the accuracy and no time to develop such an algorithm, the rules found by PRIM were tested in a simplified way: The rules were applied to 10 new sets of 10 000 futures. The density and coverage of the subgroups were then measured and compared to that of the original PRIM-box. The tests showed no significant variation in the density or coverage when the rules were applied to new datasets.

9.3.3 Sobol Sensitivity Analysis

To examine the sensitivity of R_{CCS} and R_{CCU} with respect to changes in the uncertain parameters, the first, second, and total order sensitivity indices were calculated. The sample size had to be notably high (1 000 000 samples) for the indices to converge.

9.3.4 Why Robustness was Not Investigated

For this analysis, it would be possible to compare the CCS and CCU investments, as well as the investment years 2030 and 2040, and search for the most robust investment strategy. However, concerns were discovered regarding this. Firstly, comparing the NPVs of CCS and CCU was deemed as potentially misleading. This was because the NPVs showed great dependence on the eSAF and CRC price ranges chosen. These are in turn greatly uncertain, and little information was found to back up the assumptions about their ranges. Hence, the comparison was deemed inappropriate.

Secondly, comparing an investment in CCS(CCU) in 2030 and an investment in CCS(CCU) in 2040 also raised concerns. To make a fair comparison, a simulation would have to be made over the same time period, which in this case (considering the investments having a 20-year useful lifetime) would be years 2030-2060. However, if investing in CCS 2030, TvAB is faced with a new investment decision in 2050. As it was beyond the scope of this study to evaluate the potential value of another investment in 2050, it was not possible to compare the robustness of investing in 2030 versus 2040.

9.4 Step 5: New Futures and Strategies

The last step of RDM is the proposing of new futures and strategies. Although the uncertainties and model were iterated over the course of the study, no new strategies were proposed as this was beyond the scope of the study. Similarly, RDM highlights the benefit of adaptive strategies to achieve robustness. However, developing adaptive strategies was also beyond the study scope.

10 Model Building

In short, the model constructed in Rhodium consists of cashflows related to the CCU/S investments, which are then used to calculate NPV and Regret. To be able to compare investments made in 2030 and 2040, the change in cashflows over time had to be considered. Due to the limited scope of this study, only a selection of factors is modelled as functions of time, namely the development of carbon capture and electrolyser capital expenses, the amount of fossil CO_2 captured, as well as electricity and ETS prices. This will be further described in the following section, where the NPV calculations are presented.

10.1 NPV Calculations

10.1.1 NPV of Not Investing

The cashflows of not investing are restricted to the costs of emission allowances TvAB must pay for the fossil CO_2 not stored or used for eSAF production. Both the ETS price as well as the amount of fossil CO_2 captured are modelled as functions of time (see section 10.2.2 *Modelling of Uncertainties*) and are noted $pETS(t)$ and $fCO_2(t)$ respectively. This results in the following NPV of not investing, named $NPV_{n.i.}$:

$$NPV_{n.i.} = \sum_{t=t_{inv}}^{T} \frac{-fCO_2(t) \cdot pETS(t))}{(1+DR)^t}$$

10.1.2 NPV of CCS Investment

In the following, the cashflows considered for the CCS investment are described, followed by the NPV calculation.

Carbon Capture Costs

The costs of carbon capture consist of capital expenses (*CAPEX*), operational expenses (*OPEX*), electricity costs, and steam costs. The capital expenses are a function of investment year t_{inv} and noted $CAPEX_{CC}(t_{inv})$. It is multiplied by an annuity factor A to yield an annual *CAPEX* expense. The annuity factor is calculated as:

$$A = \frac{r \cdot (1+r)^T}{(1+r)^T - 1}$$

where r is the interest rate and T the number of payment periods, which in this case is the same as the carbon capture unit's useful lifetime in years.

Meanwhile, *OPEX* is assumed to be 4% of *CAPEX*. Regarding the electricity costs, since the annual amount of captured CO_2 is constant, the electricity consumption, $cElec_{CC}$, is assumed to be constant, whereas the electricity price, $pElec(t)$, is a function of time. Steam costs, $pSteam$, are also assumed to be constant. Thus, the annual costs of carbon capture can be described as:

$$pCC(t, t_{inv}) = A \cdot CAPEX_{CC}(t_{inv}) + 0.04 \cdot CAPEX_{CC}(t_{inv}) + cElec_{CC} \cdot pElec(t) + pSteam$$

Transport and Storage Costs

The costs of CO_2 transport and storage are modelled as an annual mean cost kept constant over the whole simulation period (although in reality costs might change over time e.g. due to development in CCS infrastructure). Thus, with *TS* being the transport and storage costs per kg CO_2 and tCO_2 the total amount of CO_2 captured yearly, the annual transport and storage costs are $TS \cdot tCO_2$.

CRC Revenue

As described in section 7.5 *The CRC Market*, there are great uncertainties regarding the possible cashflows from CRCs. One way to stress-test the CCS investment would be to have randomised price developments. However, with completely random price developments, a way to identify the relationship between Regret and CRC price could not be found. To make the results more interpretable, the revenue from CRC is simplified and described as a constant annual income which could be interpreted as a mean income over the CCS investment's useful lifetime. The amount of captured biogenic CO_2, however, is modelled as a function of time. Noting the biogenic CO_2 as $bCO_2(t) = tCO_2 - fCO_2(t)$, the annual revenue from CRCs is described as $bCO_2(t) \cdot pCRC$.

NPV of CCS Investment

Considering all the mentioned costs and revenues, the NPV of a CCS investment is calculated as:

$$NPV_{CCS} = \sum_{t=t_{inv}}^{T} \frac{bCO_2(t) \cdot pCRC - (\ pCC(t, t_{inv}) + TS \cdot tCO_2\ )}{(1 + DR)^t}$$

10.1.3 NPV of CCU Investment

Carbon Capture Costs

For CCU, the carbon capture costs are calculated in the same way as for the CCS investment.

H_2 Production Costs

The costs of hydrogen production consist of electrolyser *CAPEX* and *OPEX*, costs of extending the power grid, water costs, and electricity costs. The *CAPEX* depends both on the installed capacity, $C_{H2,MW}$, and investment year t_{inv}. Noting the *CAPEX* per installed MW as $CAPEX_{H2,MW}(t_{inv})$, the specific *CAPEX* of the electrolyser is:

$$CAPEX_{H2,spec}(t_{inv}) = C_{H2,MW} \cdot CAPEX_{H2,MW}(t_{inv})$$

The *OPEX* is then calculated as 3% of the specific CAPEX. The water and power grid expenses, pWP, as well as the annual electricity consumption, $cElec_{H2}$, are regarded as constant while the electricity price $pElec(t)$ is a function of time. Again, the *CAPEX* is multiplied by an annuity factor *A*. Thus, the final H2 costs are:

$$pH_2(t, t_{inv}) = A \cdot CAPEX_{H2,spec}(t_{inv}) + 0.03 \cdot CAPEX_{H2,spec}(t_{inv}) + pWP + cElec_{H2} \cdot pElec(t)$$

Fuel Synthesis Costs

Both the costs of synthesising one kilogram of fuel, $pSynth$, as well as the amount of fuel produced yearly, F_{out}, are assumed to be constant, giving annual synthesis costs: $pSynth \cdot F_{out}$.

ETS Costs

Since the use of eSAF does not prevent the utilised carbon from entering the atmosphere, TvAB would still have to pay emission allowances for the fossil CO_2 used in eSAF production. Thus, the ETS-costs in year *t* are: $fCO_2(t) \cdot pETS(t)$.

Fuel Revenues

It is assumed that the mass output from the fuel synthesis, F_{out}, consists of eSAF and naphtha only. The price of naphtha is regarded as constant with a value based on the global average price of naphtha between 2017 and 2023.

The price of eSAF is also modelled as a constant. In early versions of the model, attempts were made to capture the dynamics of the eSAF market, including the potential prices of other eSAFs. This would then be used to estimate a maximum price TvAB could put on their eSAF. However, during a meeting with TvAB, it was expressed that they would only invest in CCU if the ReFuelEU Aviation regulation is in place, including the punishment for not following the synthetic SAF mandate. Consequently, it is assumed that there are clear incentives for buying eSAF in the case of a CCU investment, even if the price is high. However, even with this assumption it is difficult to predict the price TvAB could put on their eSAF. Thus, to simplify the model, all market dynamics are excluded, and the selling price of eSAF is modelled as a constant with an uncertainty range.

With the Y_{eSAF} and $Y_{naphtha}$ being the yield of eSAF and naphtha, and $peSAF$ and $pNaphtha$ their price, the revenue from the produced fuel is described as:

$$F_{revenue} = F_{out} \cdot Y_{eSAF} \cdot peSAF + F_{out} \cdot Y_{naphtha} \cdot pNaphtha$$

10.1.4 NPV of CCU Investment

Considering all costs and revenues, the NPV of the CCU investment is calculated as:

$$NPV_{CCU} = \sum_{t=t_{inv}}^{T} \frac{F_{revenue} - [pCC(t, t_{inv}) + pH_2(t, t_{inv}) + pSynth \cdot F_{out} + fCO_2(t) \cdot pETS(t)]}{(1 + DR)^t}$$

10.1.5 NPV Calculations - Summary

Table 7 summarises the equations related to the NPV calculations presented. Explanations and units of the parameters included in these equations are summarised in section ii. *Abbreviations Appearing in Part III*.

Table 7. Summary of equations related to NPV calculations.

NPV of not investing	$NPV_{n.i.} = \sum_{t=t_{inv}}^{T} \frac{-fCO_2(t) \cdot pETS(t))}{(1+DR)^t}$
NPV of CCS	$NPV_{CCS} = \sum_{t=t_{inv}}^{T} \frac{bCO_2(t) \cdot pCRC - (pCC(t,t_{inv}) + TS \cdot tCO_2)}{(1+DR)^t}$
Related equations	$pCC(t,t_{inv}) = A \cdot CAPEX_{CC}(t_{inv}) + 0.04 \cdot CAPEX_{CC}(t_{inv}) + cElec_{CC} \cdot pElec(t) + pSteam$
	$A = \frac{r \cdot (1+r)^T}{(1+r)^T - 1}$
NPV of CCU	$NPV_{CCU} = \sum_{t=t_{inv}}^{T} \frac{F_{revenue} - [pCC(t,t_{inv}) + pH_2(t,t_{inv}) + pSynth \cdot F_{out} + fCO_2(t) \cdot pETS(t)]}{(1+DR)^t}$
Related equations	$F_{revenue} = F_{out} \cdot Y_{eSAF} \cdot peSAF + F_{out} \cdot Y_{naphtha} \cdot pNaphtha$
	$pCC(t,t_{inv}) = A \cdot CAPEX_{CC}(t_{inv}) + 0.04 \cdot CAPEX_{CC}(t_{inv}) + cElec_{CC} \cdot pElec(t) + pSteam$
	$A = \frac{r \cdot (1+r)^T}{(1+r)^T - 1}$
	$pH_2(t,t_{inv}) = A \cdot CAPEX_{H2,spec}(t_{inv}) + 0.03 \cdot CAPEX_{H2,spec}(t_{inv}) + pWP + cElec_{H2} \cdot pElec(t)$
	$CAPEX_{H2,spec}(t_{inv}) = C_{H2,MW} \cdot CAPEX_{H2,MW}(t_{inv})$

10.2 NPV Input Values

In the following, the values of the parameters used to calculate NPV_{CCS} and NPV_{CCU} are presented, starting with the factors that are kept constant, followed by static and time-dependent uncertainties.

10.2.1 Parameters Kept Constants

Table 8 presents the model parameters that are kept constant due to various reasons, for example the value was considered rather certain, the uncertainty was not believed to have a notable influence on the output, the uncertainty was not of interest, or it was beyond the scope of this study. Values that are internal to TvAB are marked as “internal data”.

Table 8. Values of the model parameters that are kept constant. X marks values that are internal to TvAB.

Parameter	Description	Value	Source
tCO_2	Amount of captured CO_2	250 000 t/year	Given by TvAB
T	Useful lifetime	20 years	Given by TvAB
DR	Discount rate	5%	Given by TvAB
r	Interest rate	6%	Given by TvAB
A	Annuity factor	0,0872	Given by $A = \frac{r \cdot (1+r)^T}{(1+r)^T - 1}$
$cElec_{CC}$	CC electricity consumption	X MWh/year	Internal data
$pSteam$	CC Steam costs	X SEK/year	Internal data
pWP	Electrolyser water and power grid expenses	X SEK/year	Internal data
$cElec_{H2}$	Electrolyser electricity consumption	X MWh/year	Internal data
$pSynth$	Fuel synthesis costs	X SEK/kg_{fuel}	Internal data
F_{out}	Fuel output from fuel synthesis	X kg/year	Internal data
Y_{eSAF}	Yield eSAF	70% by mass	Based on assumption made by (Project SkyPower 2024).
$Y_{naphtha}$	Yield naphtha	30% by mass	Assumption
pNaphtha	Naphtha price	5 SEK/kg	Based on the global average price of naphtha between 2017 and 2023 (Krungsri Research 2024) and converted from USD/t to SEK(2025)/kg

10.2.2 Modelling of Uncertainties

In Rhodium, parameters defined as uncertainties can be assigned a distribution of values. In accordance with the RDM framework, all uncertain parameters are given a uniform distribution defined by a minimum and maximum value. As mentioned earlier, some parameters are modelled as changing with time. Thus, a distinction is made between static and dynamic uncertainties, both of which are presented in the following.

Static Uncertainties

Table 9 shows the uncertainties that are modelled as mean values over the whole useful lifetime, as well as their uncertainty ranges. The main reason for these being static is the lack of information regarding their future development (for details, see section 10.1 *NPV Calculations*).

Table 9. Value ranges of the uncertainties that do not change with time.

Parameter	Abbreviation	Range	Source
Transport and storage costs	*TS*	X ± 30% MSEK/year	Internal data.
CRC selling price	*pCRC*	800-5000 SEK/t	Assumption. The maximum value is based on the maximum mean of the modelled ETS prices between 2030 and 2060, which is ~4500 SEK/t.
e-SAF selling price	*peSAF*	40-90 SEK/kg	Assumption. Range based on the minimum and maximum projected eSAF prices as displayed in Figure 10.

Dynamic Uncertainties

As earlier mentioned, the parameters modelled as changing with time are the carbon capture and electrolyser CAPEX, the fraction of fossil CO_2, as well as electricity and ETS prices. Why these are chosen to be dynamic and how they are modelled will now be presented.

Modelling of CC and electrolyser CAPEX

Since the CAPEXs of a carbon capture and electrolysis facility present the largest capital expenses in a CCS and CCU investment respectively, it was decided to consider the potential cost reduction these could experience over time. One common way to model development of technological costs is through learning curves (Lee, Chun, Roh, Heo & Lee 2023). These models assume that the cost declines continuously, either as a function of cumulative installed capacity (learning by doing, LBD) or cumulative patent applications (also called learning by research) (Liu, Zhang, Li, Chen & Teng 2022). LBD follows a power law (Lee et al. 2023) such that the cost of a particular technology decreases as more units of the same type are built. When the technology is mature, there is little room for more learning, and the cost approaches a stable value (Beiron & Johnsson 2024).

Due to the limited study scope, the projected increase in electrolysis and carbon capture facilities or patent applications is not considered. Instead, to keep the model simple yet capture the continuous cost decline moving towards a steady cost level, the carbon capture and electrolysis CAPEX are assumed to decline by a set percentage each year. Specifically, the CAPEX of carbon capture, if investing in year t_{inv}, is calculated as:

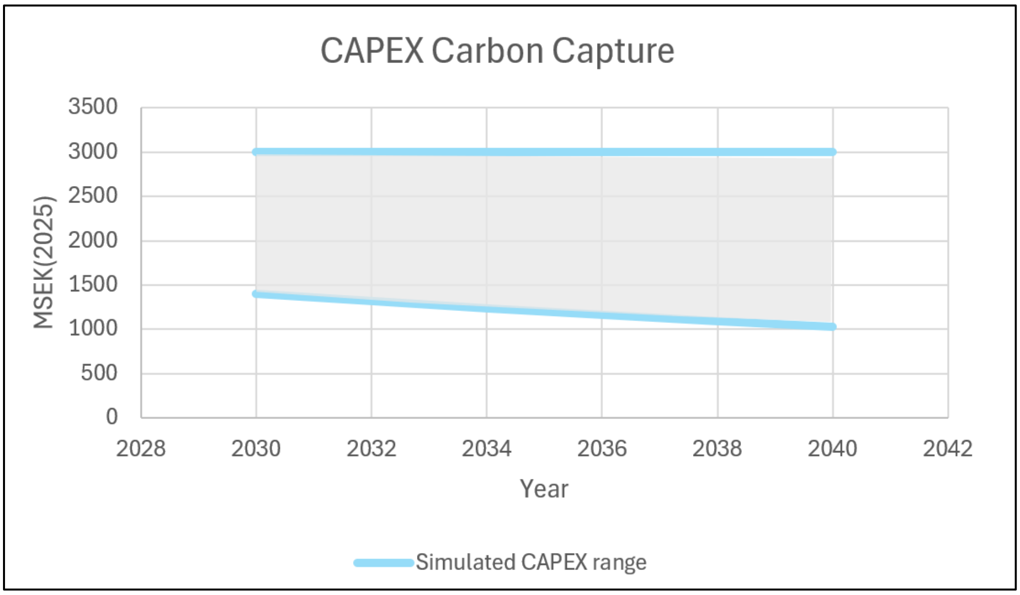
$$CAPEX_{CC}(t_{inv}) = C_0 \cdot (C_{RR})^{(t_{inv}-t_0)}$$

and the CAPEX of an electrolyser as:

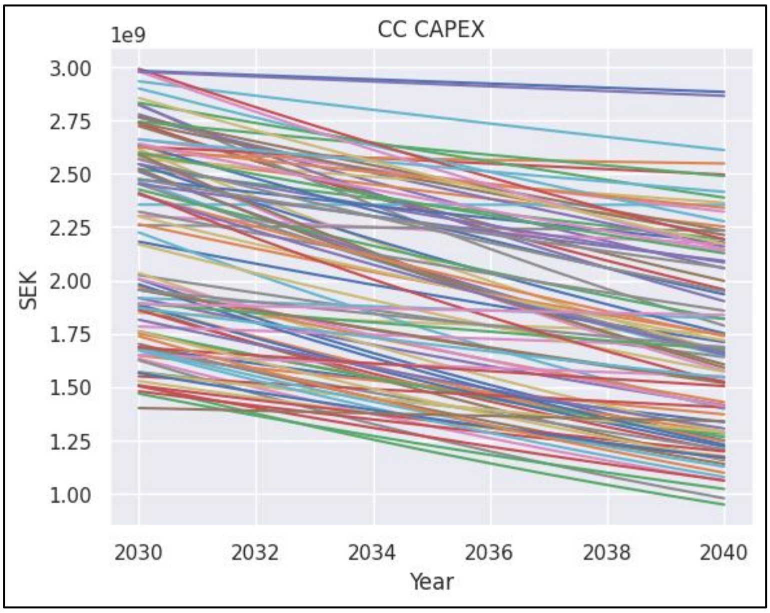
$$CAPEX_{H2,MW}(t_{inv}) = E_0 \cdot (E_{RR})^{(t_{inv}-t_0)}$$

Here, C_0 and E_0 are CAPEXs in year $t_0 = 2030$ whereas C_{RR} and E_{RR} are fixed annual price reduction rates.

For the CC CAPEX, C_0 and C_{RR} are considered uncertain and given ranges such that the curves are found in the area shown in Figure 18a). It should be noted that the uncertainty in C_0 also captures the potential of receiving reduced CC-CAPEX through funding. (For specific values of C_0 and C_{RR}, see *Appendix A4*). Figure 18b) shows a collection of simulated CAPEX curves.



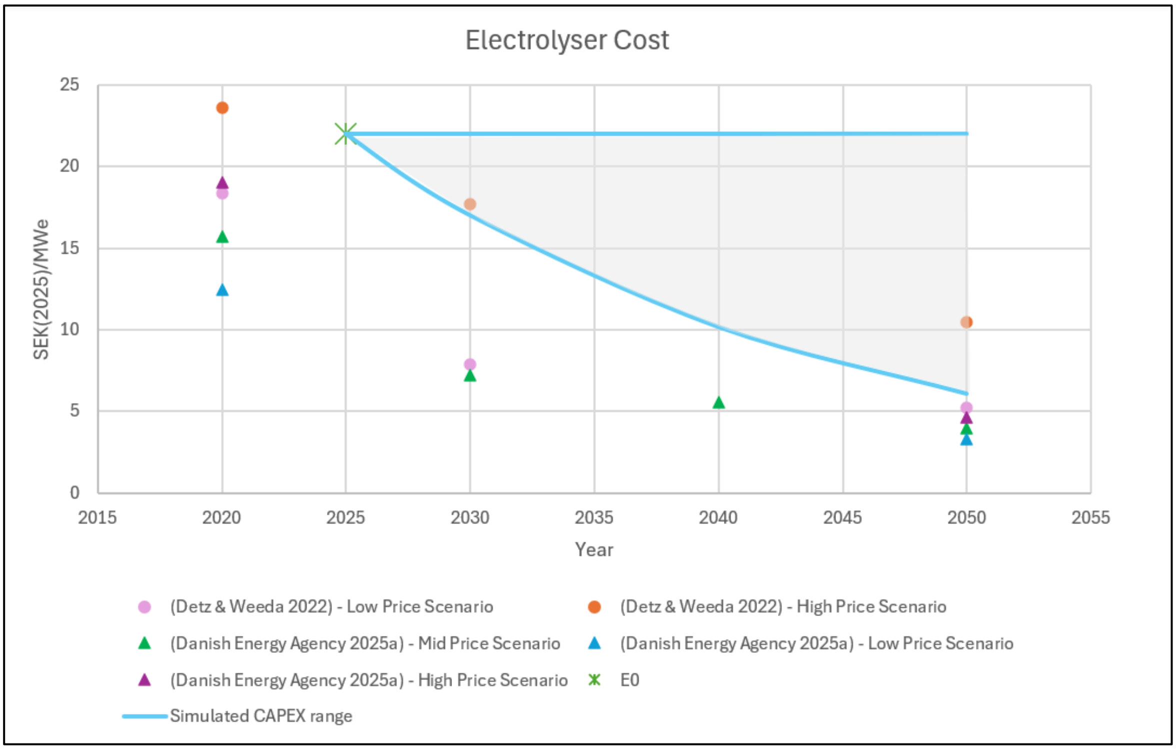
a)



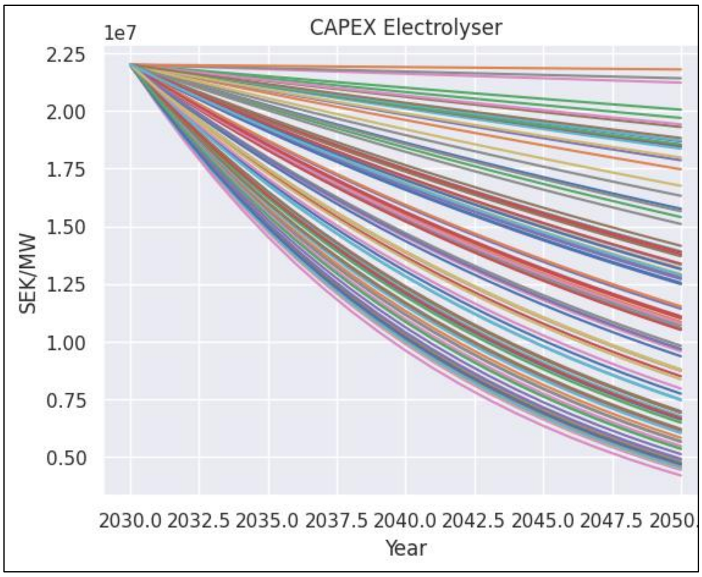
b)

Figure 18. a) The range of simulated carbon capture CAPEXs. b) Carbon capture CAPEX curves simulated in Rhodium.

Unlike the carbon capture investment cost, the electrolyser cost in 2030 is based on internal data and does not include any uncertainty. The same goes for the electrolyser capacity, which is chosen such that if operating 8000 hours/year, the produced H_2 will be enough to convert all 250 000 tonnes captured CO_2 into fuel. Thus, the only uncertainty in the electrolyser CAPEX lies in the cost reduction rate E_{RR}. This value was roughly based on predictions from the literature analysis (section 7.2 *Uncertainties Related to Electrolyser Investment Costs*). Figure 19a) shows the results from the literature analysis as well as the chosen range for potential CAPEX curves. Figure 19b) shows a collection of simulated CAPEX curves. (For specific values, see *Appendix A5*.)



a)



b)

Figure 19. a) The range of simulated electrolyser CAPEXs as well as the estimated price developments presented by the Danish Energy Agency (2025a) and Detz & Weeda (2022) (for further details see section 7.2 Uncertainties Related to Electrolyser Investment Costs). b) Electrolyser CAPEX curves simulated in Rhodium.

Modelling of captured fossil CO_2

The fraction of fossil versus biogenic CO_2 captured affects both CCS and CCU investments, as this is related to CRC revenue and ETS costs. It was desired to explore various scenarios, both where the fraction of fossil CO_2 decreases and increases. However, as it was beyond the scope of this study to investigate what this development could look like, it was assumed to be linear. Figure 20 shows examples of how the development of captured fossil CO_2 has been modelled. The ranges of values determining the curves are presented in *Appendix A3*.

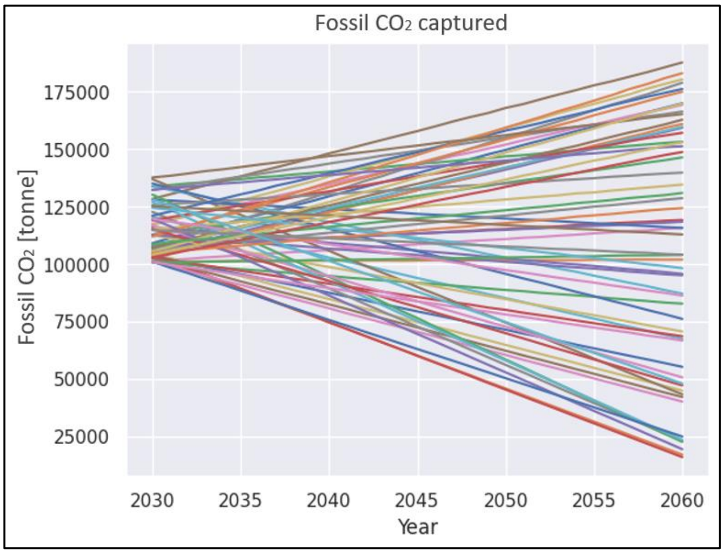


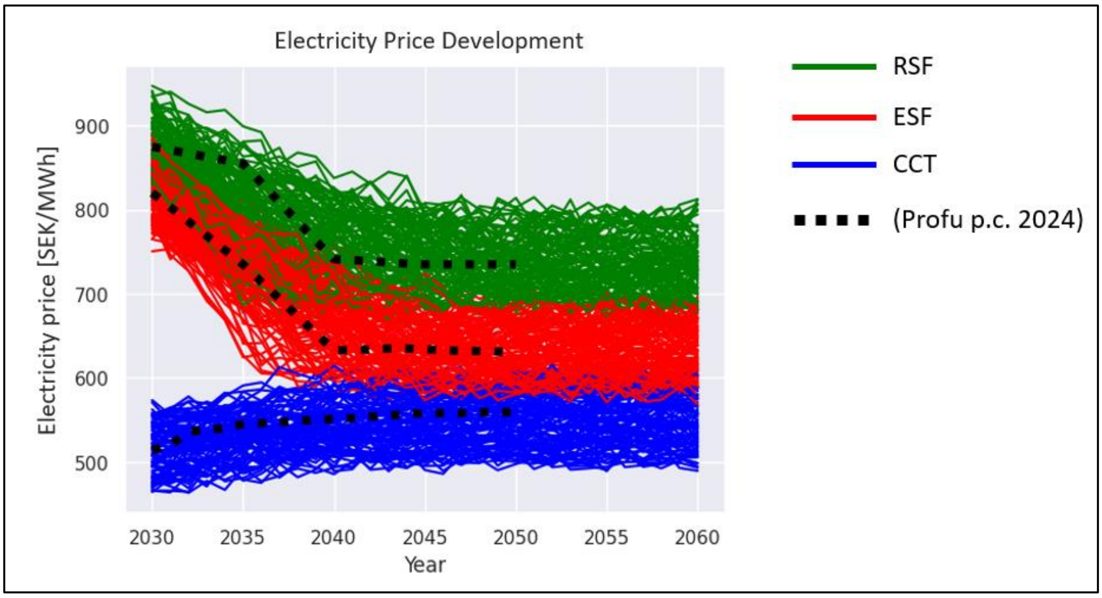
Figure 20. Development of the amount of captured CO_2 from fossil sources as simulated in Rhodium.

ETS and electricity prices

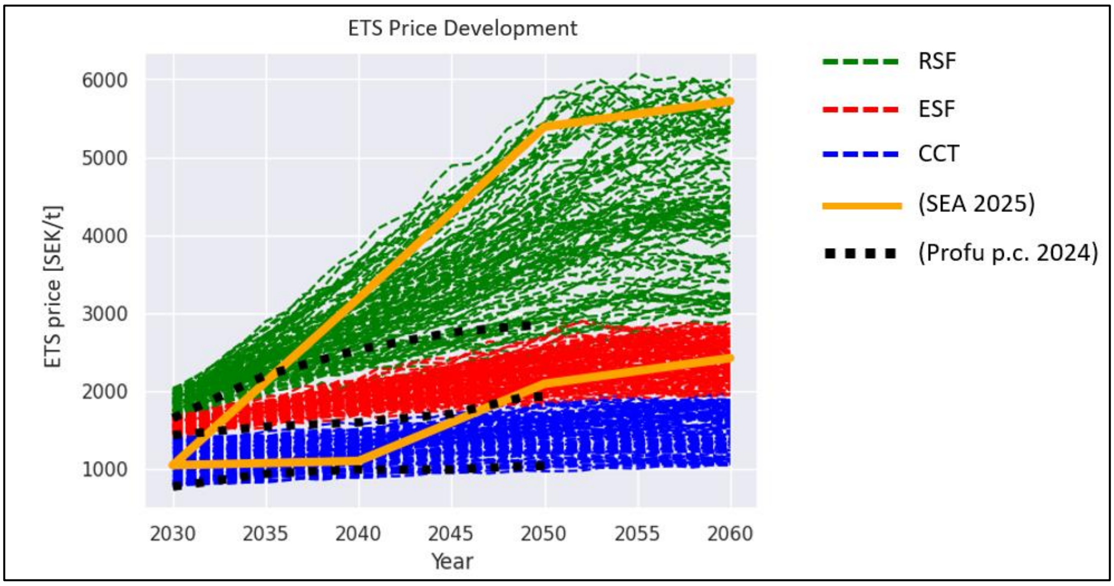
As mentioned in section 7.4 *Uncertainties in ETS and Electricity Prices*, uncertainties in ETS and electricity prices are highlighted as important for investments in CCS and eSAF production. Consequently, their change with time is considered. Three trends are investigated based on the scenarios identified by Bisaillon et al. from Profu – RSF, ESF and CCT. One major reason is that each of these scenarios has one electricity and one ETS price curve related to it. By having this grouping of cost projections, the relationship between electricity and ETS prices could also be captured.

As can be seen from the electricity price predictions presented by (Profu p.c. 2024) (see Figure 7, section 7.4.3 *Scenario Based Modelling of ETS and Electricity Prices*), the electricity prices seem to stabilise around 2040. Similarly, if considering the predicted ETS-price development presented by (SEA 2025b) (see Figure 8), the ETS prices seem to become more stable around 2050. To capture this, a helping function generating the development of ETS and electricity prices between 2030 and 2060 was developed. The function is given a start value, a year when the curve will reach a plateau, the value of this plateau, and a volatility value to capture any price volatility. Using this function, a variety of cost curves could be generated whilst keeping some resemblance to those presented by (Profu p.c. 2024) and (SEA 2025b).

The electricity price curves are based on the estimates by (Profu p.c. 2024). Figure 21a) shows a collection of simulated electricity curves as well as the predictions they are based on. In contrast, the ETS prices are built on the predictions presented by (SEA 2025b) and (Profu p.c. 2024) as this resulted in a larger price range being examined. Since the scenarios WAM and RSF both are futures where EU climate ambitions are prioritised, they are assumed to be similar. Thus, the RSF scenario as adapted in this model is extended to include the WAM ETS price trajectory. This is displayed in Figure 21b), which shows the modelling in practice. The ranges of inputs to the helping function are presented in *Appendix A1 and A2*.



a)



b)

Figure 21. a) Electricity price developments as simulated in Rhodium, as well as price predictions by Profu (p.c. 2024). b) ETS price developments as simulated in Rhodium, as well as predicted price developments presented by Profu (p.c. 2024) and the Swedish Energy Agency (2025b).

10.3 Minimum and Maximum Mean Annual Costs

Finally, to get an idea of the costs in relation to each other, the minimum and maximum mean annual costs of CCS and CCU in the 12 investigated cases are shown in Figure 22 and Figure 23 respectively. It should be noted that these are approximate mean costs over the 20-year useful lifetime and do not consider the time value of money. As such, these figures only serve the purpose of giving the reader an idea of the costs in relation to each other. Moreover, for CCU, the ETS costs have been excluded. Figure 24 and Figure 25 show the difference between the minimum and maximum mean annual costs of CCS and CCU respectively. Again, this aims to give an indication of the potential cost increases or reductions.

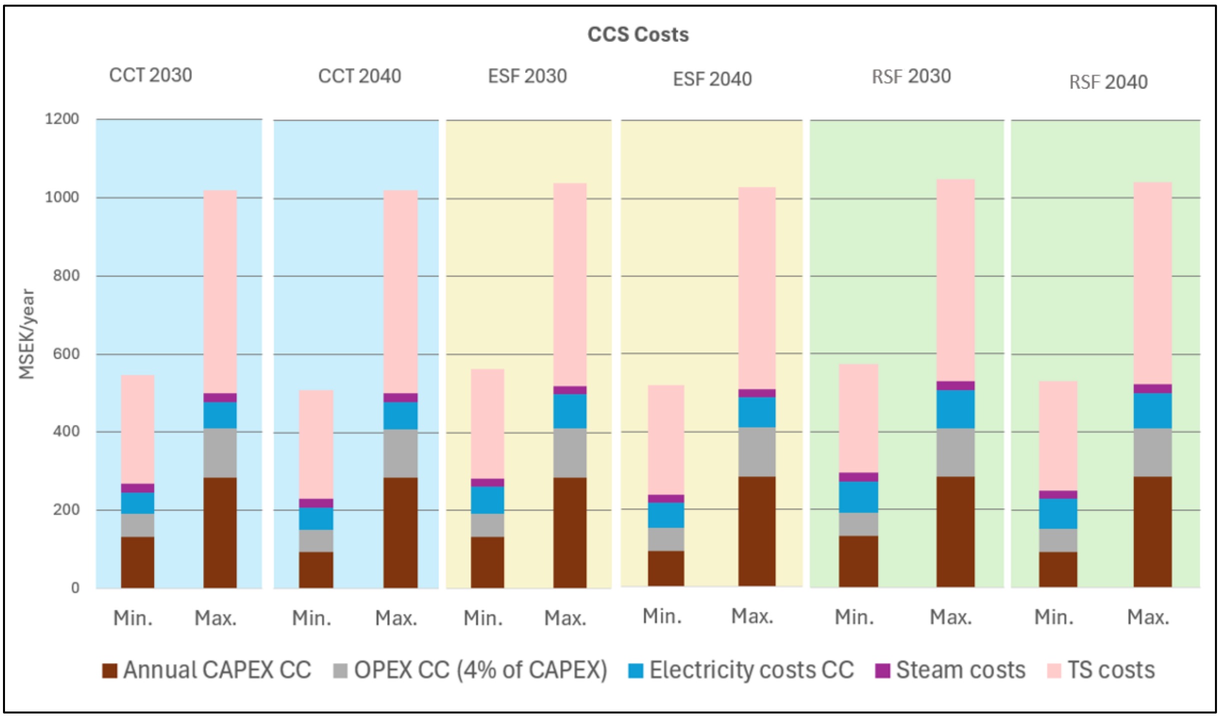


Figure 22. Minimum and maximum mean annual costs of CCS. Note, these values do not consider the time value of money.

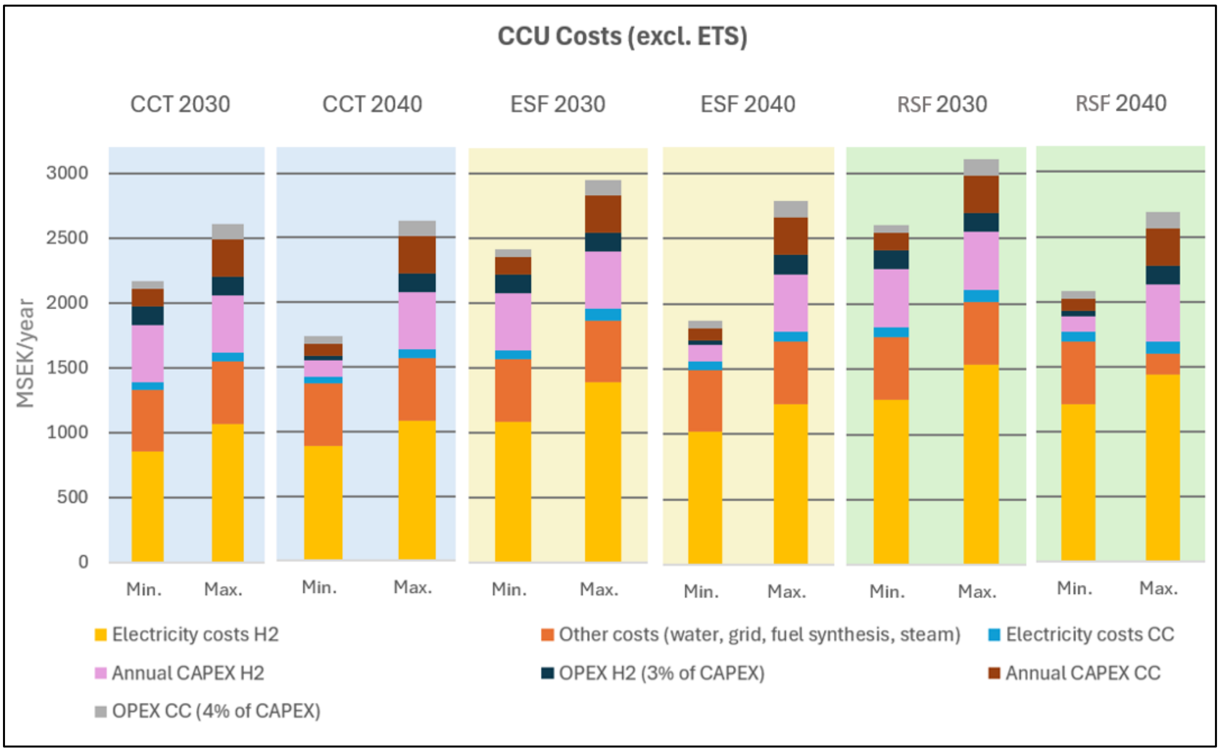


Figure 23. Minimum and maximum mean annual costs of CCU. Note, these values do not consider the time value of money and exclude ETS costs.

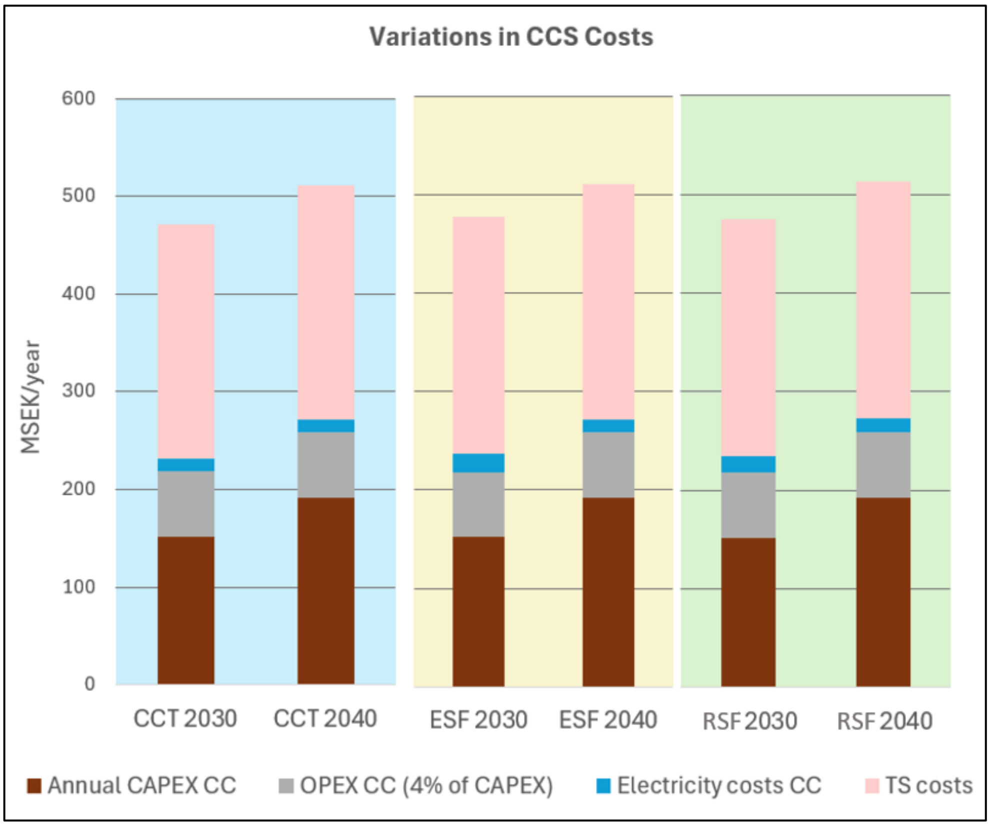


Figure 24. Difference between the minimum and maximum mean annual costs of CCS. Note, these values do not consider the time value of money.

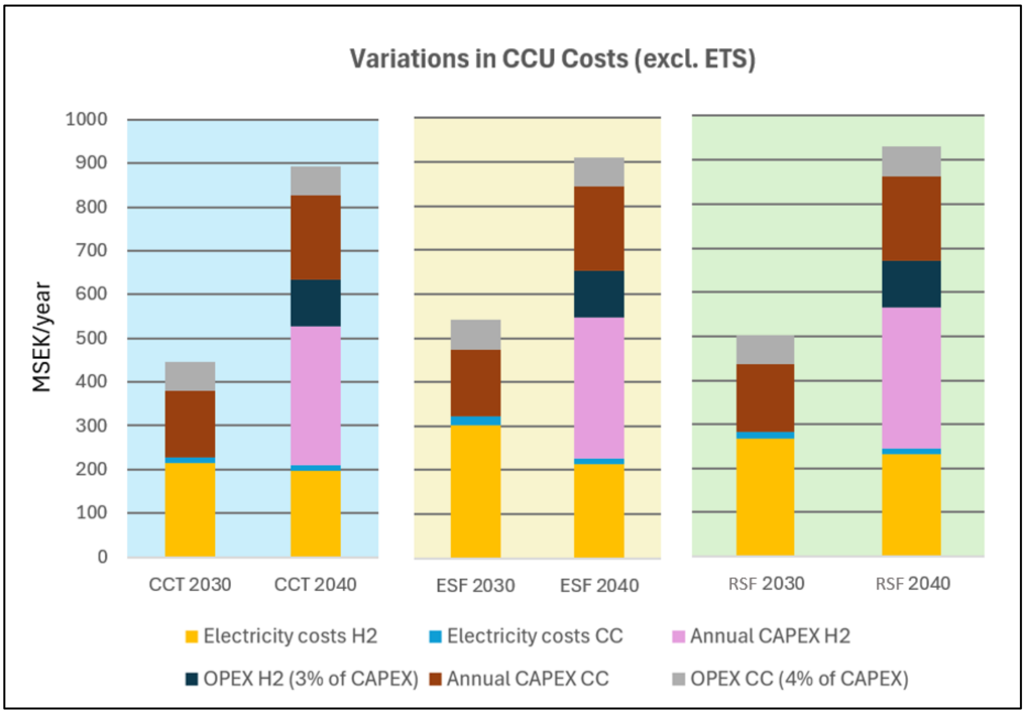


Figure 25. Difference between the minimum and maximum mean annual costs of CCU. Note, these values do not consider the time value of money and exclude ETS costs.

Part IV: RDM Analysis - Results

11. Results

In the following, results from the simulations, Sobol sensitivity analyses and CART and PRIM analyses are presented, starting with the results related to CCS. Table 10 gives a description of parameter abbreviations used in this section. These are also given in section iii. *Abbreviations Appearing in Part IV*.

Table 10. Description of parameter and scenario abbreviations used in the Results section.

	Parameter	Unit	Description
Uncertainties	C0	SEK	Carbon capture CAPEX year 2030
	CRR	-	Carbon capture CAPEX annual price reduction rate
	fCO2_2030	t_{CO2}/year	Fraction fossil CO_2 out of annual captured CO_2 year 2030
	fCO2_2060	t_{CO2}/year	Fraction fossil CO_2 out of annual captured CO_2 year 2060
	pCRC	SEK/t_{CO2}	Price of carbon credits
	pElec_2030	SEK/MWh	Mean electricity price year 2030
	pElec_dt	-	Electricity price volatility
	pElec_vPlat	SEK/MWh	Value of electricity price plateau
	pElec_yPlat	year	Year electricity price plateau is reached
	pETS_2030	SEK/MWh	Mean ETS price year 2030
	pETS_dt	-	ETS price volatility
	pETS_vPlat	SEK/MWh	Value of ETS price plateau
	pETS_yPlat	year	Year ETS price plateau is reached
	TS	SEK/t_{CO2}	Transport and storage costs
	peSAF	SEK/kg_{eSAF}	Price of eSAF
	ERR	-	Electrolyser CAPEX annual price reduction rate
Other	R_{CCS}	SEK	Regret of investing in CCS as compared to not investing
	R_{CCU}	SEK	Regret of investing in CCU as compared to not investing
	S_T	-	Total sensitivity index
	S_2	-	Second order sensitivity index
Scenario abbreviation			**Description**
CCT 2030			Electricity and ETS scenario CCT. Investment made in year 2030
CCT 2040			Electricity and ETS scenario CCT. Investment made in year 2040
ESF 2030			Electricity and ETS scenario ESF. Investment made in year 2030
ESF 2040			Electricity and ETS scenario ESF. Investment made in year 2040
RSF 2030			Electricity and ETS scenario RSF. Investment made in year 2030
RSF 2040			Electricity and ETS scenario RSF. Investment made in year 2040

11.1 CCS

In the following, the results from analysing the decision of investing in CCS or not are presented.

11.1.1 Sobol Sensitivity Analysis

Figure 26 shows the total sensitivity index (S_T) of the uncertainties investigated for CCS. To recall, these refer to the sensitivity of R_{CCS} with respect to changes in the uncertain parameters. In Figure 27, the second-order sensitivity indices (S_2) with a value above 0.01 are shown. The values of all sensitivity indices calculated are included in *Appendix B1*.

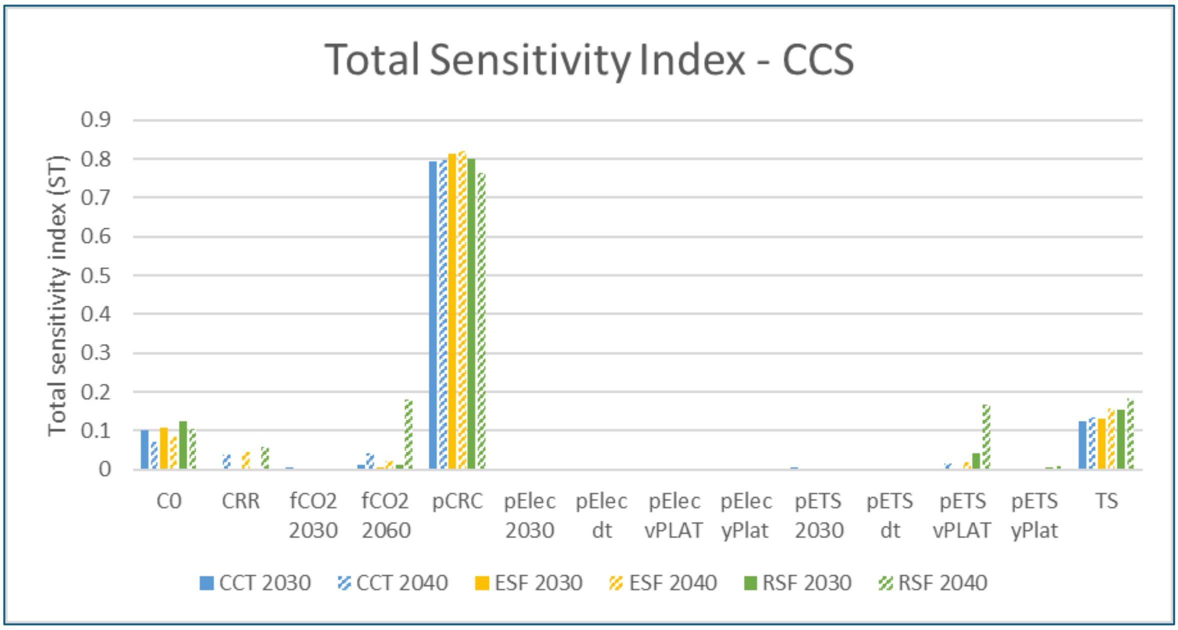


Figure 26. Total sensitivity indices of uncertainties related to CCS investment. Refers to the sensitivity of the regret of investing in CCS (R_{CCS}) with respect to the uncertain parameters.

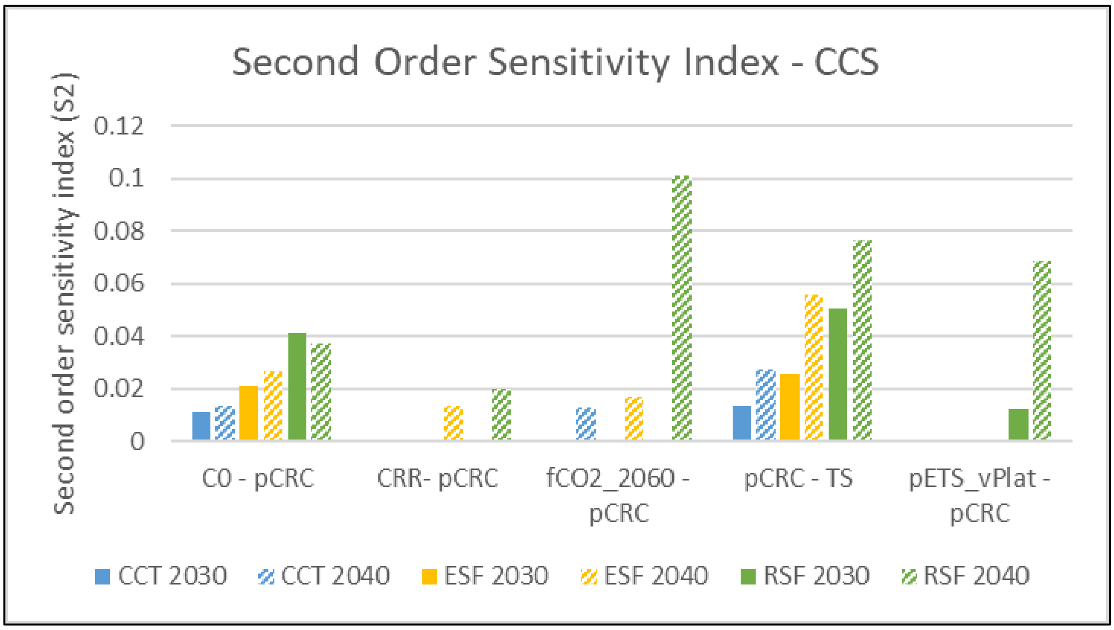


Figure 27. Second-order sensitivity indices of CCS-related uncertainties with a value above 0.01. Refers to the sensitivity of the regret of investing in CCS (R_{CCS}) with respect to the uncertain parameters.

11.1.2 CART

As the trees produced by CART are large and difficult to display, they are instead presented in table format in *Appendix B2*. Figure 28 shows the results from the feature score analyses. Only feature scores with a value above 0,01 are included. As mentioned in section 8. *Tools of RDM Analysis*, a high feature score indicates that a parameter is an important predictor of what class the target variable belongs to – in this case $R_{CCS} = 0$ or $R_{CCS} > 0$.

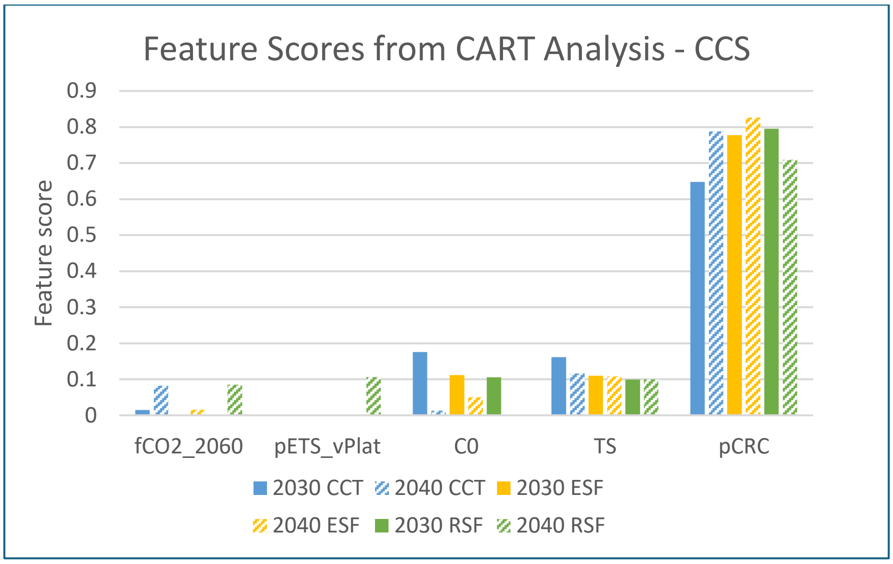


Figure 28. Feature scores with a value above 0.01. These relate to CART trees where the case of interest is $R_{CCS} = 0$.

11.1.3 PRIM

As mentioned earlier, two PRIM analyses are performed. In the first, the aim is to find under what conditions the Regret of investing in CCS is zero. The results from the first analysis are summarised in Figure 29 and Table 11. In Figure 29, each bar represents a restriction in the parameter's range. The value displayed by the bar is the value of the restriction, while the length of the bar puts this value in relation to the parameter's minimum and maximum value, referred to as MIN and MAX. For instance, the first bar to the left in Figure 29 indicates that in case CCT 2030, the range of the parameter *pCRC* is reduced from 800-5000 SEK/t to 3950-5000 SEK/t through the restriction $pCRC \geq 3{,}95$ kSEK/t. Together, parameter restrictions characterise a group of futures where 90% of them result in $R_{CCS} = 0$.

Moreover, Figure 29 includes the Density and Coverage of these groups, referred to as *D* and *C* respectively. Table 11 contains all parameter restrictions as well as their ranges and qp-values. Similarly, the results of analysing conditions for $R_{CCS} > 0$ are presented in Figure 30 and Table 12.

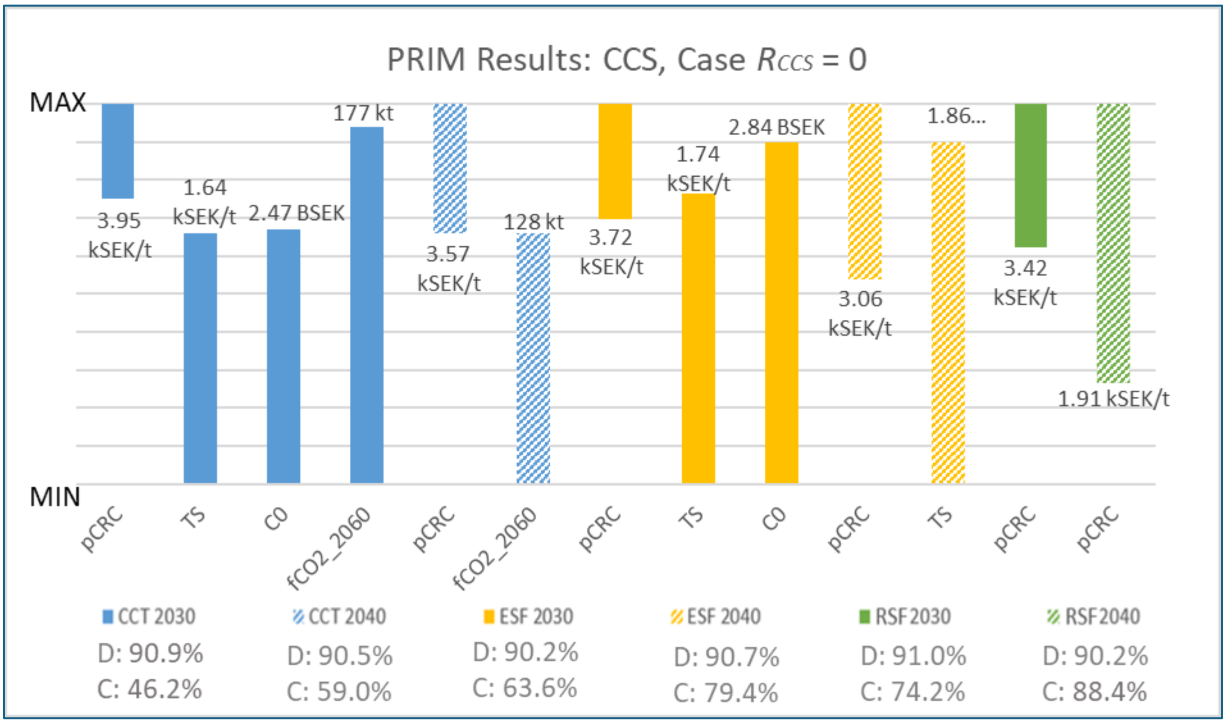


Figure 29. Visualisation of the PRIM results with the case of interest $R_{CCS} = 0$. The value displayed by each bar is the value of the parameter restriction, while MIN and MAX refer to the parameters' minimum and maximum values. D and C stand for Density and Coverage respectively.

Table 11. Results from PRIM analysis with case of interest $R_{CCS} = 0$.

PRIM Results CCS: $R_{CSS} = 0$						
Case	**Dens.**	**Cov.**	**Parameter**	**Range**	**Rule**	**qp-value**
CCT 2030	90.9%	46.2%	*pCRC*	0.8-5 kSEK/t	pCRC ≥ 3.95 kSEK/t	0
			TS	1.05-1.95 kSEK/t	TS ≤ 1.64 kSEK/t	$3.37 \cdot 10^{-33}$
			C0	1.40-3.00 BSEK	C0 ≤ 2.47 BSEK	$8.30 \cdot 10^{-22}$
			fCO2_2060	12.5-188 kt	fCO2_2060 ≤177 kt	0.154
CCT 2040	90.5%	59.0%	*pCRC*	0.8-5 kSEK/t	pCRC ≥ 3.57 SEK/t	0
			fCO2_2060	12.5-188 kt	fCO2_2060 ≤128 kt	$1.09 \cdot 10^{-51}$
ESF 2030	90.2%	63.6%	*pCRC*	0.8-5 kSEK/t	pCRC ≥ 3.72 kSEK/t	0
			TS	1.05-1.95 kSEK/t	TS ≤ 174 kSEK/t	$3.21 \cdot 10^{-25}$
			C0	1.40-3.00 BSEK	C0 ≤ 2.84 BSEK	$4.15 \cdot 10^{-5}$
ESF 2040	90.7%	79.4%	*pCRC*	0.8-5 kSEK/t	pCRC ≥ 3.06 kSEK/t	0
			TS	1.05-1.95 kSEK/t	TS ≤ 1.86 kSEK/t	$1.75 \cdot 10^{-10}$
RSF 2030	91.0%	74.2%	*pCRC*	0.8-5 kSEK/t	pCRC ≥ 3.42 kSEK/t	0
RSF 2040	90.2%	88.4%	*pCRC*	0.8-5 kSEK/t	pCRC ≥ 1.91 kSEK/t	$2.19 \cdot 10^{-240}$

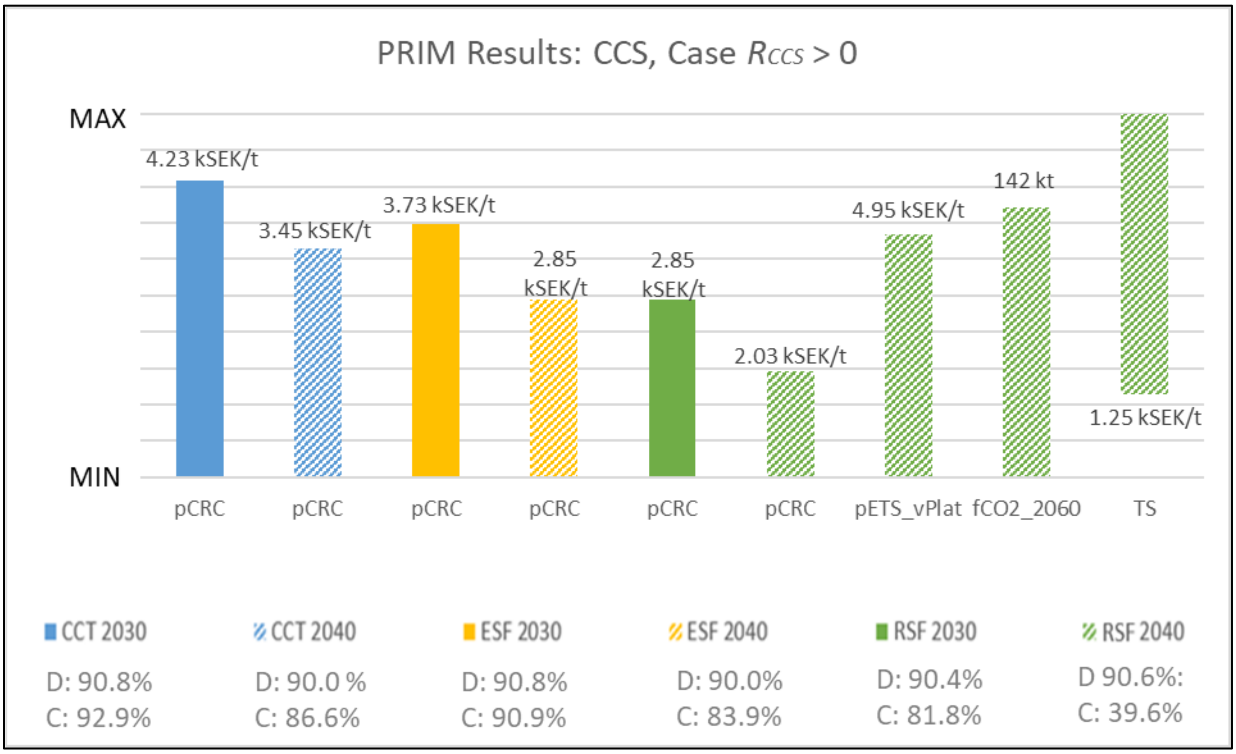


Figure 30. Visualisation of the PRIM results with the case of interest $R_{CCS} > 0$. The value displayed by the bar is the value of the parameter restriction, while MIN and MAX refer to the parameters' minimum and maximum values. D and C stand for Density and Coverage respectively.

Table 12. Results from PRIM analysis with case of interest $R_{CCS} > 0$.

PRIM Results CCS: $R_{CCS} > 0$						
Case	**Dens.**	**Cov.**	**Parameter**	**Range**	**Rule**	**qp-value**
CCT 2030	90.8%	92.9%	*pCRC*	0.8-5 kSEK/t	pCRC ≤ 4.23 kSEK/t	$6.72 \cdot 10^{-167}$
CCT 2040	90.0%	86.6%	*pCRC*	0.8-5 kSEK/t	pCRC ≤ 3.45 SEK/t	0
ESF 2030	90.8%	90.9%	*pCRC*	0.8-5 kSEK/t	pCRC ≤ 3.73 kSEK/t	0
ESF 2040	90.0%	83.9%	*pCRC*	0.8-5 kSEK/t	pCRC ≤ 2.85 kSEK/t	0
RSF 2030	90.4%	81.8%	*pCRC*	0.8-5 kSEK/t	pCRC ≤ 2.85 kSEK/t	0
RSF 2040	90.6%	39.6%	*pCRC*	0.8-5 kSEK/t	pCRC ≤ 2.03 kSEK/t	$3.30 \cdot 10^{-305}$
			pETS_vPlat	2.84-6.00 kSEK/t	pETS_vPlat ≤ 4.95 SEK/t	$1.98 \cdot 10^{-16}$
			fCO2_2060	12.5-188 kt	fCO2_2060 ≤142 kt	$2.00 \cdot 10^{-14}$
			TS	1.05-1.95 kSEK/t	TS ≤ 1.25 kSEK/t	$4.65 \cdot 10^{-9}$

11.1.4 Plots

Figure 31 shows the simulation results where each point represents a simulated future, and the colour is a measure of the Regret of investing in CCS. Purple points indicate futures where it is preferable to invest in CCS, and non-purple dots where it is preferable not to invest. The y- and x-axes show the value of the parameter with the greatest and second-greatest S_T-value respectively. Lastly, Figure 32 shows for each examined case the percentage of futures where $R_{CCS} = 0$.

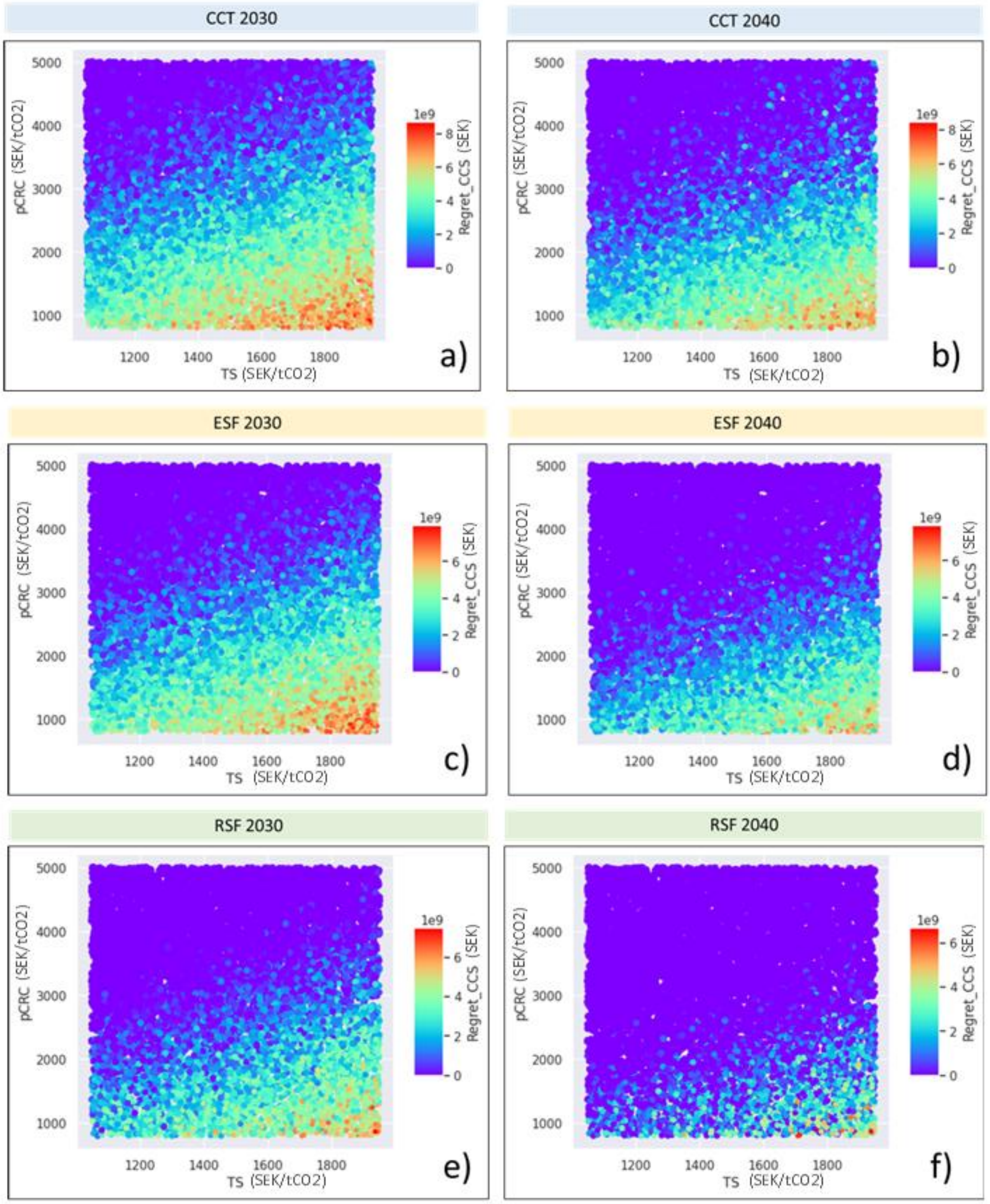


Figure 31. Plots showing the relationship between R_{CCS} and the two uncertainties with the largest total sensitivity index in case: a) CCT 2030, b) CCT 2040, c) ESF 2030, d) ESF 2040, e) RSF 2030, f) RSF 2040.

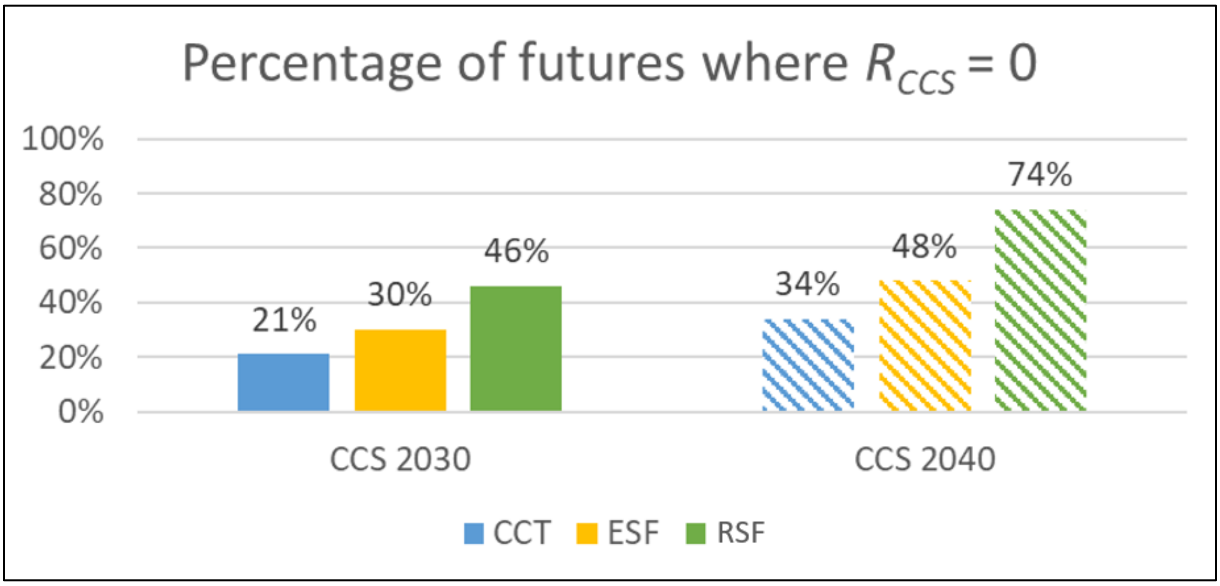


Figure 32. The percentage of futures where R_{CCS} = 0.

11.1.5 Comments on CCS Results

As seen in Figure 26 and Figure 27, R_{CCS} appears to be most sensitive to the CRC price. Moreover, in all cases, the Regret shows some sensitivity to transport and storage costs and the investment cost of carbon capture. Comparing this to Figure 23, these are also factors making up large fractions of the difference between minimum and maximum CCS costs.

For the case RSF 2040, the fraction fossil CO_2 year 2060 (*fCO2_2060*) and ETS plateau value (*pETS_vPlat*) also have notable S_T values. These are mainly attributable to interactions with the CRC price, as indicated in Figure 27. The interaction between *pETS_vPlat* and *pCRC* could reflect that if both have a high value, investing in CCS is favoured (since high emission fees are avoided and a high income is received from carbon credits). Similarly, if both are low not investing is favoured. The interactions between *pCRC* and *fCO2_2060* could arise because a low *fCO2_2060* means that more CRCs can be sold. However, in all other cases, Regret barely shows any sensitivity to the ETS price or the development of fossil CO_2. One reason could be that in the case RSF 2040, the ETS price has the largest range and could contribute more to the output variance.

The results from the Sobol sensitivity analysis are similar to the CART feature scores shown in Figure 28. For instance, the CRC price has the highest feature score, whereas transport and storage and carbon capture CAPEX show lower but notable feature scores.

From the PRIM analysis, a couple of things can be noticed. First, looking at Figure 29 and considering investment years 2030 and 2040 separately, the range given the carbon credit price increases from scenario CCT to RSF. I.e. if comparing case RSF to CCT, the lower limit in carbon credit price can decrease and still it would be possible to find a group of futures where 90% result in zero Regret in CCS. This aligns with Figure 31 which shows that R_{CCS} = 0 cases (purple points) start to appear at lower carbon credit prices when moving from scenario CCT through RSF. Since the scenarios define electricity and ETS price trends, this would be due to electricity or ETS prices. However, as can be seen from Figure 22, electricity costs only make up a small fraction of the total CCS costs. Instead, the reason could be that emission fees are low in case CCT, higher in ESF and the highest in RSF. High emission costs disfavour not investing, making CCS preferable even when the revenue from carbon credits is lower.

Naturally, a similar pattern can be seen in Figure 30 where the maximum price put on carbon credits decreases when moving from scenario CCT to RSF. However, these price maxima are higher than the price minima in Figure 29. This would be due to the boxes defined in Figure 29, including some of the bad cases covered by the box in Figure 30. Moreover, as displayed in Table 12, going from CCT 2030 to RSF 2040, the coverage decreases from 92,9% to 39,6%. This can be explained by comparing Figure 31a) and Figure 31e), where in the first figure there is an area with high density in $R_{CCS} > 0$ futures, whereas in the second figure this area is sparser. To capture an area with high density, many $R_{CCS} > 0$ cases are not included, resulting in low coverage. To be more risk-averse, investigating $R_{CCS} > 0$ cases with high coverage should be prioritised over high density.

Moreover, comparing the investment years within each scenario, Figure 30 shows that the range given the carbon credit price is smaller when investing in 2040 compared to 2030. Since the Regret in CCS is sensitive to carbon capture CAPEX, this would likely be due to the carbon capture CAPEX being lower in 2040 than in 2030. These patterns regarding the carbon credit price can also be observed in Figure 32, which suggests that CCS is preferable in an RSF scenario.

It is worth noting that the rules found by PRIM depend on the density and coverage one chooses to examine. Moreover, it also depends on the parameter ranges chosen. For instance, if the maximum carbon credit price is increased above 5000 SEK/tonne, the number of $R_{CCS} = 0$ cases would increase. Then, the minimum carbon credit price could be decreased while maintaining a 90% density in $R_{CCS} = 0$ cases. Similarly, the PRIM results could change with model simulations. Although a test was applied to show that a found ruleset worked well on other datasets, running the PRIM analysis on different datasets would give slightly different rulesets. Unfortunately, how large those variations could be was not investigated.

11.2 CCU

In the following, the results from analysing the decision of investing in CCU or not are presented.

11.2.1 Sobol Sensitivity Analysis

Figure 33 shows the total sensitivity index (S_T) of the uncertainties investigated for CCU. These refer to the sensitivity of R_{CCU} with respect to changes in the uncertain parameters. In Figure 34, the second-order sensitivity indices (S_2) with a value above 0.01 are shown. The values of all sensitivity indices calculated are included in *Appendix B1*.

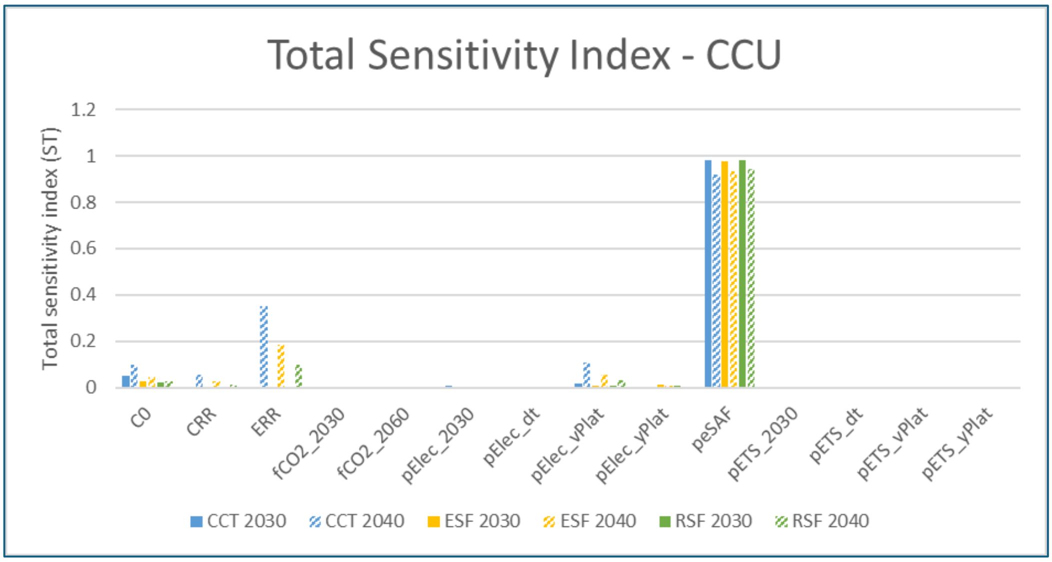


Figure 33. Total sensitivity indices of uncertainties related to CCU investment. Refers to the sensitivity of the regret of investing in CCU (R_{CCU}) with respect to the uncertain parameters.

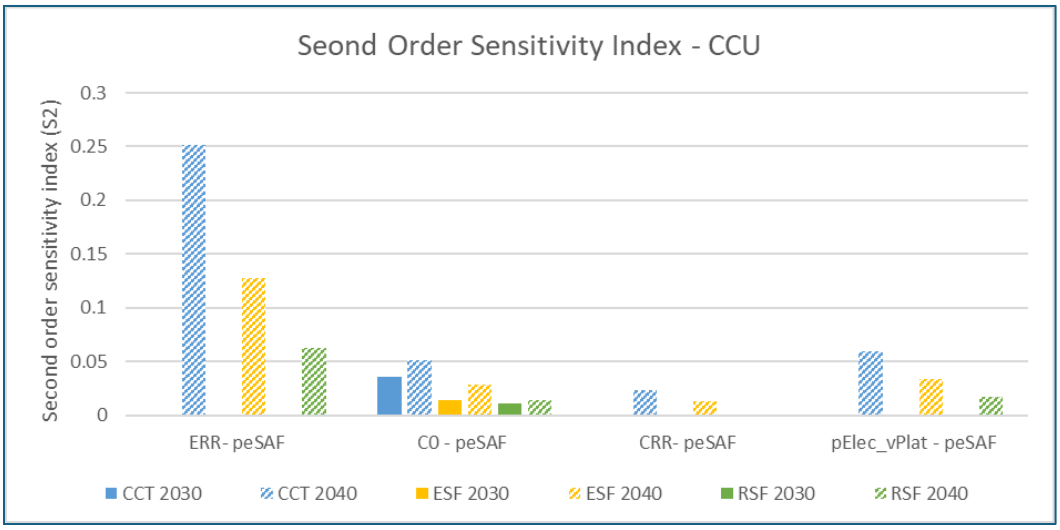


Figure 34. Second-order sensitivity indices of CCU-related uncertainties with a value above 0.01. Refers to the sensitivity of the regret of investing in CCU (R_{CCU}) with respect to the uncertain parameters.

11.2.2 CART

As mentioned earlier, due to the trees produced by CART being large and difficult to display, they are presented in table format in *Appendix B2*. Figure 35 shows the results from the feature score analyses, including feature scores with a value above 0.01. The feature scores relate to trees predicting futures where $R_{CCS} = 0$.

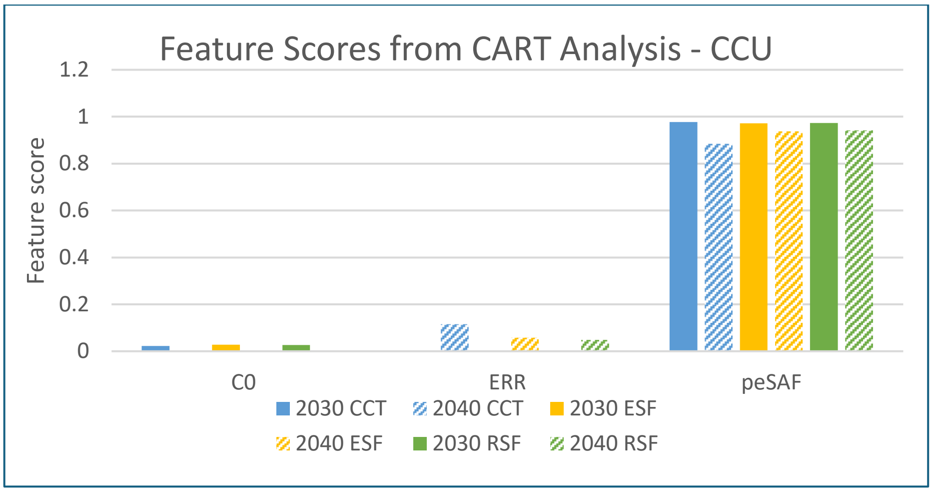


Figure 35. Feature scores with a value above 0.01. These relate to CART trees classifying futures where R_{CCU} = 0 from futures where R_{CCU} > 0.

11.2.3 PRIM

The results from the PRIM analysis when investigating conditions for $R_{CCU} = 0$ are presented in Figure 36 and Table 13. The results from examining the conditions for $R_{CCU} > 0$ are shown in Figure 37 and Table 14. A more detailed explanation of how to interpret Figure 36 and Figure 37 is presented in section 11.1.3 *PRIM*.

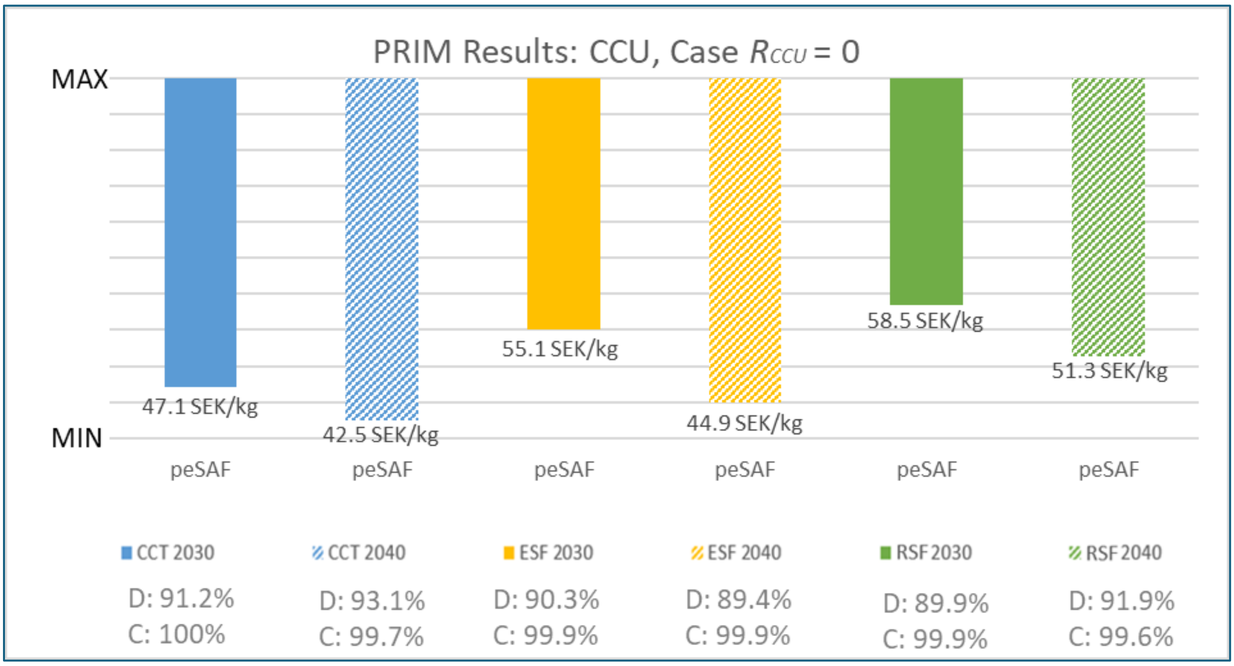


Figure 36. Visualisation of the PRIM results with the case of interest R_{CCU} = 0. The value displayed by the bar is the value of the parameter restriction, while MIN and MAX refer to the parameters' minimum and maximum values. D and C stand for Density and Coverage respectively.

Table 13. Results from PRIM analysis with case of interest R_{CCU} = 0.

PRIM Results CCU: R_{CCU} = 0						
Case	**Dens.**	**Cov.**	**Parameter**	**Range**	**Rule**	**qp-value**
CCT 2030	91.2%	100%	*peSAF*	40-90 SEK/kg	peSAF ≥ 47.1 SEK/kg	$5.56 \cdot 10^{-228}$
CCT 2040	93.1%	99.7%	*peSAF*	40-90 SEK/kg	peSAF ≥ 42.5 SEK/kg	$2.52 \cdot 10^{-47}$
ESF 2030	90.3%	99.9%	*peSAF*	40-90 SEK/kg	peSAF ≥ 55.1 SEK/kg	0
ESF 2040	89.4%	99.9%	*peSAF*	40-90 SEK/kg	peSAF ≥ 44.9 SEK/kg	$4.29 \cdot 10^{-111}$
RSF 2030	89.9%	99.9%	*peSAF*	40-90 SEK/kg	peSAF ≥ 58.5 SEK/kg	0
RSF 2040	91.9%	99.6%	*peSAF*	40-90 SEK/kg	peSAF ≥ 55.3 SEK/kg	0

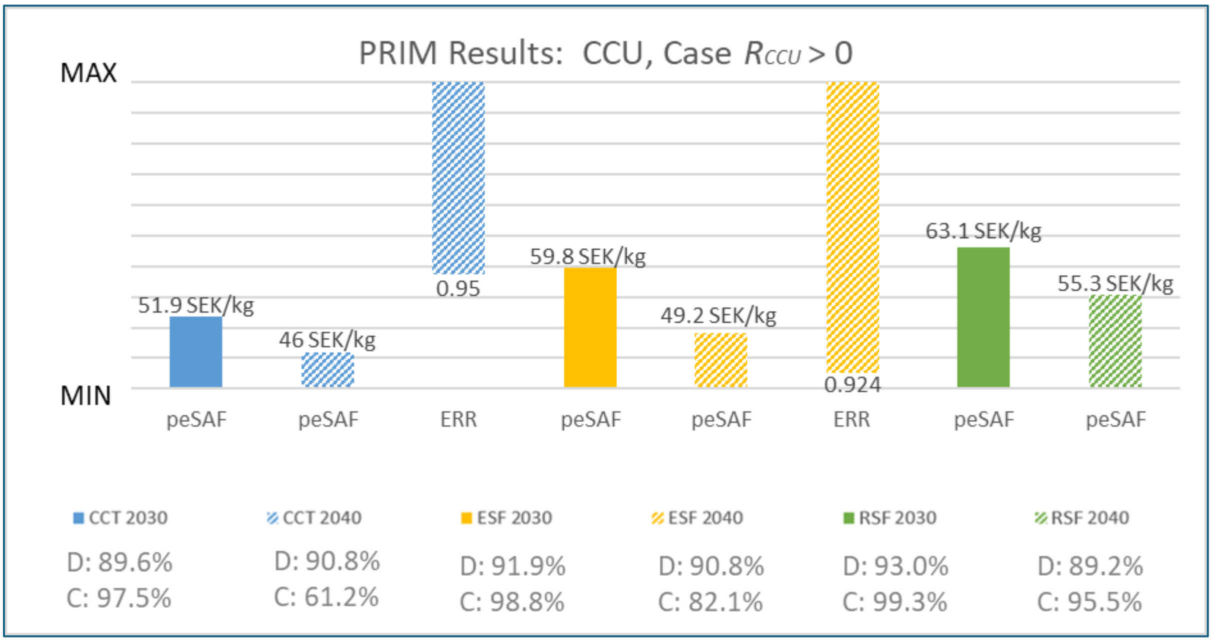


Figure 37. Visualisation of the PRIM results with the case of interest R_{CCU} > 0. The value displayed by the bar is the value of the parameter restriction, while MIN and MAX refer to the parameters' minimum and maximum values. D and C stand for Density and Coverage respectively.

Table 14. Results from PRIM analysis with case of interest R_{CCU} > 0.

PRIM Results CCU: R_{CCU} > 0						
Case	**Dens.**	**Cov.**	**Parameter**	**Range**	**Rule**	**qp-value**
CCT 2030	89.6%	97.5%	*peSAF*	40-90 SEK/kg	peSAF ≤ 51.9 SEK/kg	0
CCT 2040	90.8%	61.2%	*peSAF*	40-90 SEK/kg	peSAF ≤ 46.0 SEK/kg	0
			ERR	0.92-1	ERR ≥ 0.95	$4.54 \cdot 10^{-22}$
ESF 2030	91.9%	98.8%	*peSAF*	40-90 SEK/kg	peSAF ≤ 55.1 SEK/kg	0
ESF 2040	90.8%	82.1%	*peSAF*	40-90 SEK/kg	peSAF ≤ 49.2 SEK/kg	0
			ERR	0.92-1	ERR ≥ 0.92.4	$3.55 \cdot 10^{-2}$
RSF 2030	93.0%	99.3%	*peSAF*	40-90 SEK/kg	peSAF ≤ 63.1 SEK/kg	0
RSF 2040	89.2%	95.5%	*peSAF*	40-90 SEK/kg	peSAF ≤ 55.3 SEK/kg	0

11.2.4 Plots

In Figure 38, each point represents a simulated future, and the colour is a measure of the Regret of investing in CCU. Purple points indicate futures where it is preferable to invest in CCU, and non-purple dots where it is preferable not to invest. The y- and x-axes show the value of the parameter with the greatest and second-greatest S_T-value respectively. Lastly, for each of the examined cases, Figure 39 shows the percentage of futures where R_{CCS} = 0.

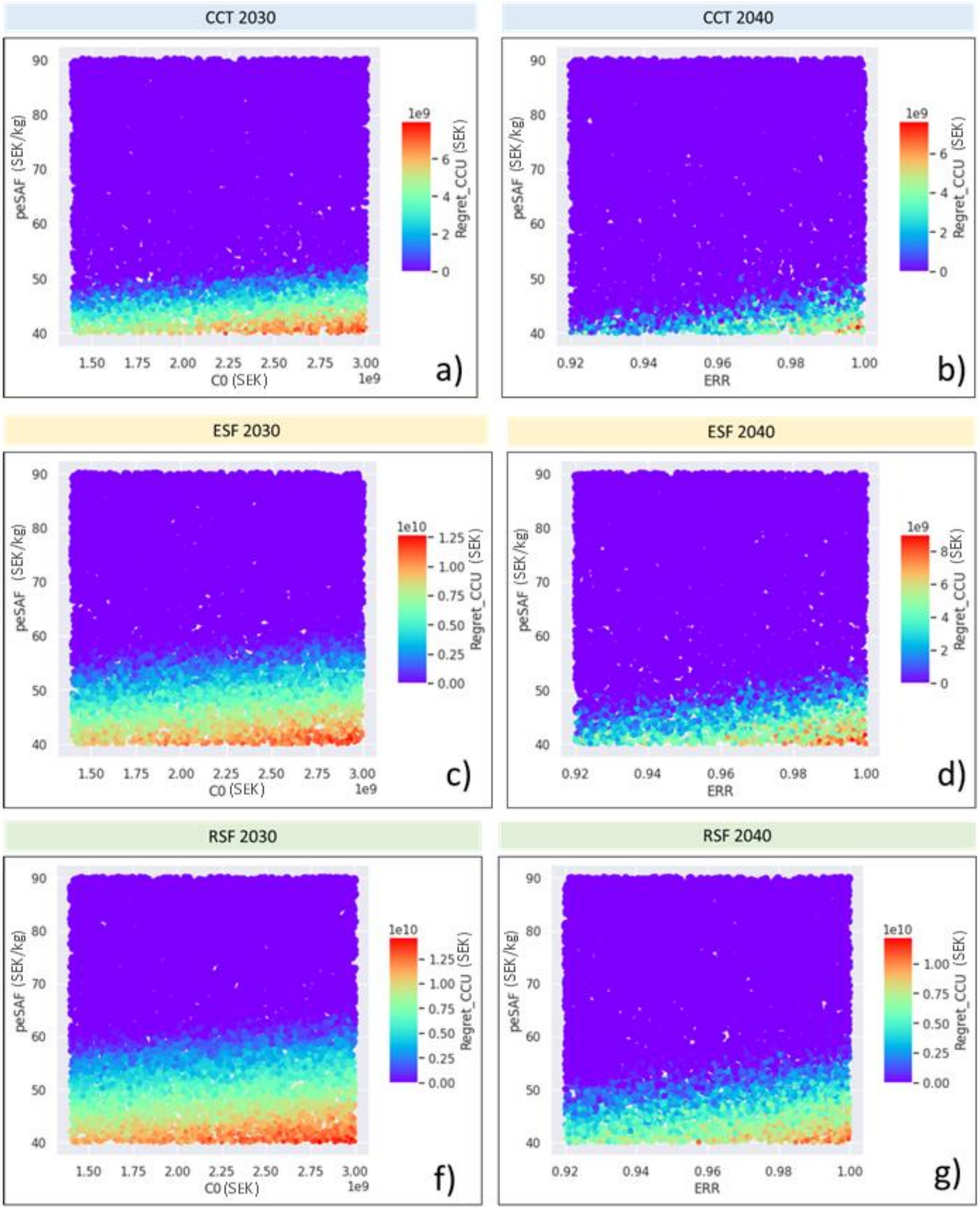


Figure 38. Plots showing the relationship between R_{CCU} and the two uncertainties with the largest total sensitivity index in case: a) CCT 2030, b) CCT 2040, c) ESF 2030, d) ESF 2040, e) RSF 2030, f) RSF 2040.

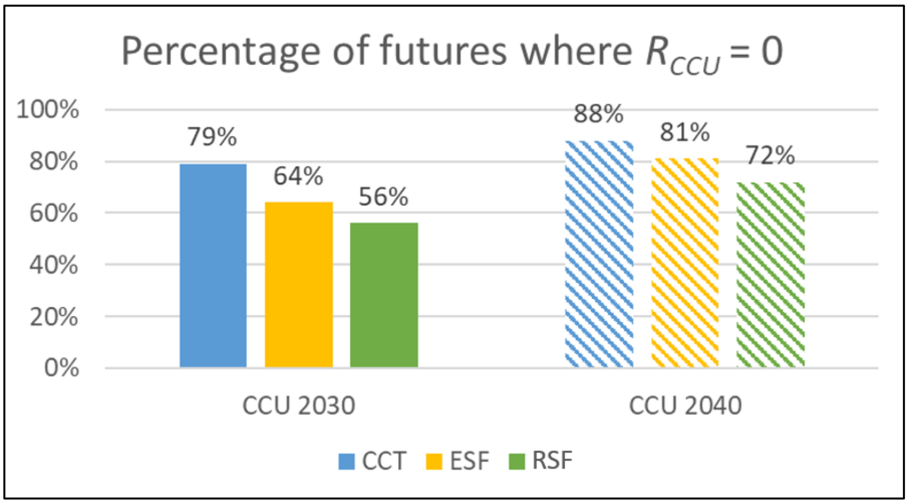


Figure 39. The percentage of futures where $R_{CCU} = 0$.

11.2.5 Comments on CCU Results

As for CCU, the sensitivity analysis shows that Regret is by far the most sensitive to the eSAF price. This would be no surprise since this is the only CCU revenue. In addition, when the investment year is 2040, R_{CCU} show sensitivity to the reduction in electrolyser price, E_{RR}. This agrees with Figure 25, which indicates that the electrolyser CAPEX has a large potential to reduce the CCU costs. Other parameters that show some sensitivity are the electricity plateau price and carbon capture CAPEX, both of which appear in Figure 25 as having notable potential to reduce eSAF production costs.

Again, the results from the sensitivity analysis align with the CART feature scores, which show that the eSAF price is the most important predictor for $R_{CCU} = 0$. Other important features are the 2030 carbon capture CAPEX and 2040 electrolyser CAPEX (i.e. E_{RR}).

As can be seen from the PRIM results displayed in Figure 36, the only rule applied is a minimum eSAF price. This is no surprise considering that the Regret in CCU is highly sensitive to the eSAF price. Moreover, going from scenario CCT to RSF, it seems like the eSAF price required to capture a scenario with 90% zero-regret cases increases. This is likely a result of higher electricity prices in cases ESF and RSF, making eSAF production more expensive. As a result, higher eSAF prices are required for the Regret to be zero.

Naturally, similar results are shown in Figure 37. However, PRIM boxes with $R_{CCU} = 0$ cases give a more optimistic eSAF price restriction than PRIM boxes containing $R_{CCU} > 0$ cases. Again, this emphasises the importance of tuning the PRIM analysis to get sufficient risk-aversion.

Once again, the patterns observed are confirmed in Figure 39, suggesting that CCU is preferable in case CCT, and that eSAF can be sold cheaper in 2040. This is likely a result of lower electricity prices in case CCT than ESF and RSF, as well as potentially cheaper electrolyser CAPEX in 2040 than 2030.

From Figure 25, it appears as if the costs of producing eSAF could be substantially reduced by a decrease in the mean electricity price. Although this could be the reason for the trend observed in Figure 39, the feature scores and sensitivity indices of the parameters related to electricity price are relatively low. This might be different if the electricity price is modelled as a mean rather than a trajectory determined by several parameters. Although this has not been confirmed, it highlights the trade-off between model complexity and interpretability. In the case of CCS, this might be the reason why the Regret shows limited sensitivity to parameters related to ETS-prices.

Part V: Discussion

12. Addressing the Research Questions

In the case of CCS, the results from the RDM analysis suggest that the price TvAB will receive for their carbon credits is crucial for the project to be favourable, even if the ETS prices are high and the fraction of biogenic carbon decreases. This highlights that insecure CRC revenue streams pose serious risks to CCS investors. At the same time, the analysis suggests that the CRC price required for CCS to be successful depends on the development of carbon capture investment costs and transportation and storage costs. It also varies between the cases CCT, ESF and RSF, likely due the scenarios' different emission fee levels. However, with the carbon credit price dominating the results, it is difficult to identify the influence of and interaction between other parameters.

Compared to investing in 2030, it seems like TvAB can sell their carbon credits at a lower price if an investment is made in 2040. The conditions causing this are likely higher ETS prices and the potential of lower carbon capture investment costs in 2040. Although this was not included in the model, CRC markets could also be more developed by 2040, providing a more solid business case for CCS. As mentioned in section 7.3 *Uncertainty in Transport and Storage Costs*, another advantage of investing later is that CCS transport and storage infrastructure could have become more developed, which could reduce costs. With the Regret showing notable sensitivity to transport and storage costs, this could prove to be important.

However, there are also potential perks of being an early mover that are not included in the model. For instance, as mentioned in section 7.3 *Uncertainty in Transport and Storage Costs*, there could be saturations along the infrastructure chain. Hence, future transport and storage costs could increase, making it preferable to invest early. Other perks could be economic support given to early movers, for instance support from innovation funds or limited funds like the Climate Leap. In addition, in the case that TvAB continues with CCS beyond 2060, they could be favoured by the gained experience. As for the model, it neglects the fact that if investing in 2030, there is another decision to be taken in 2050, which could bring value to TvAB. All in all, although the model results point to investing in 2040 being preferable, there is room for further investigation.

Similarly to CCS, the Regret of investing in CCU is dominated by one factor: the price TvAB will take for their eSAF. This will, of course, depend on what the eSAF market will look like in the future, the demand, and the price set by other producers.

The results also indicate some sensitivity to reductions in electrolyser price. However, perhaps the most important condition for eSAF production is the regulation ReFuelEU Aviation and its implementation. From the PRIM results in Figure 36, the minimum price put on eSAF ranges between 42,5-58,5 SEK/kg. Comparing this to Figure 9 showing 2024 fuel prices presented by EASA, this is still more than four times the price of conventional aviation fuel and notably higher than the price of biofuels. Although it has been beyond the scope of this study to look more closely into the future price of other SAFs and fossil aviation fuels, this points to the blending mandate and related punishments being an important condition for the case of eSAF production.

Another question arising is what political incentives for eSAF there would be in a scenario where cost consciousness is prioritised over climate ambitions. The results suggest that CCU is preferable in scenario CCT (due to lower electricity prices). Still, perhaps the assumption about there being legal incentives for eSAF production does not hold in this case, potentially making the results misleading. A possible solution would be to adapt the eSAF uncertainty range to each case – the same goes for the CRC price and perhaps even other parameters like transport and storage costs, and electrolyser CAPEX. Tuning parameters to the cases could increase interpretability and remove what is believed to be highly unlikely SOWs. On the other hand, the purpose of RDM is to stress test strategies in as wide a range of futures as possible, not to make predictions. A trade-off arises between sorting out irrelevant SOW, which could hinder analysis, and maintaining a large input space for stress-testing.

13. Limitations of the Study

The limited study scope puts restrictions on the study results. For example, only a selection of uncertainties could be considered while factors such as variations in electricity supply and uncertainties in fuel synthesis costs were neglected. Moreover, much of the modelling had to be greatly simplified due to time restrictions. For instance, it was beyond the study scope to investigate how the development of CRC and eSAF prices could be modelled. Considering the large impact these factors had on the results, these simplifications could make the results misleading. For instance, the model does not capture timely variations nor the origin of cashflows (e.g. whether the CRC price is a result of the VCM market, compliance market, or reversed auctions).

Another limitation worth mentioning is that the conditions found to be favourable for CCS or CCU are only relevant in comparison to not investing. If CCS and CCU had been compared to each other, or some other benchmark, the results would have been different. For instance, the impact of ETS prices on CCU is now nullified since ETS prices are also included in the NPV of not investing. If CCU had been compared to CCS or some other alternative where CO_2 emissions are reduced, ETS prices could turn out to be an important factor for a CCU investment.

Furthermore, although the scenarios CCT, ESF and RSF might capture some relationship between ETS prices and electricity prices, the current modelling makes it difficult to interpret the influence of ETS and electricity prices respectively. Moreover, since no other parameters are adapted to these cases, the results might be misleading. As earlier stated, a trade-off arises between sorting out what is believed to be irrelevant SOWs (e.g. a scenario where eSAF can be sold at a high price but climate ambitions are low) and exploring a wide range of futures.

Moreover, it should be noted that the literature review is not extensive, i.e. there might be relevant uncertainties that are not mentioned, or other aspects of uncertainties which are not included. The study is also restricted to an economic perspective, neglecting for example the climate impact of various investment strategies.

14. Future Research

The results show that CRC and eSAF prices are crucial for CCS and CCU investments respectively. Thus, it would be interesting to look further into how these markets could develop, what a competitive CRC and eSAF price could be, and from there, examine how TvAB could develop their business model.

Examining other performance measures could also give further insights into the investments. For instance, the benchmark could be the emission fee TvAB *currently* have to pay for 250 000 tonnes of CO_2 given the current fraction of fossil CO_2. Another alternative would be only to examine costs and exclude revenue streams – i.e. examine the *production costs* of CRCs and eSAF respectively. By excluding CRC and eSAF prices, interactions between other parameters could become more visible. It would also be interesting to further develop the scenarios – for instance how could transport and storage costs vary in the scenarios CCT, ESF, and RSF? However, there might be risks associated with leaning towards a more predictive, scenario-based approach.

Lastly, it would be interesting to investigate how TvAB could develop the CCS and CCU strategies by, for instance, using heat pumps to take care of excess heat from carbon capture or utilising the rest products from electrolysis. As for the future of Gärstadverken, there are strategies other than CCU/S that TvAB could examine, such as phasing out WtE and replacing it with biobased fuels or selling the captured CO_2 to an external actor for further usage.

15. Conclusions

To recall, the research questions of the study are:

- Under what conditions will an investment in CCS at Gärstadverken be preferable or not preferable financially in comparison to not investing?
- Under what conditions will an investment in CCU with eSAF production at Gärstadverken be preferable or not preferable financially in comparison to not investing?

To answer the first question, the RDM analysis suggests that when comparing to not investing, the factor having the greatest impact on the conditions for CCS is the revenue gained from carbon credits as generated from captured biogenic CO_2. In futures where the CRC price is high, the NPV of CCS tends to be greater than the NPV of not investing. This seems to be true even if the fraction of fossil CO_2 increases with time, resulting in fewer carbon credits. The study also investigates two investment years: 2030 and 2040. The results show that regardless of investment year, the price of carbon credits is still determinant to the decision.

However, the CRC price required for CCS to be a good investment varies with ETS and electricity trends. When the ETS and electricity prices are low, the revenue from carbon credits must be even higher in order to favour a CCS investment. Moreover, the results also suggest that the CCS investment is sensitive to carbon capture investment costs as well as transport and storage costs. When these are low, investing in CCS could be favourable even at lower CRC prices.

As for the second question, the critical condition for an investment in eSAF production is the price TvAB can take for their eSAF. This is also true regardless of investment year. However, CCU can be favourable even at lower eSAF prices if the electrolyser investment costs are low and/or if the ETS and electricity prices are low. According to the modelling, low ETS and electricity prices are associated with a scenario where Sweden and the EU prioritise economics over climate ambitions. The study does not delve into what other implications this might have, e.g. how this affects the eSAF market. Hence, there are notable limitations to the results.

To get further insights about what conditions would make CCS or CCS favourable, there is a need for model development and further investigation in market conditions for CRCs and eSAF. With a developed financial model, RDM could still provide valuable insights about investing in CCU/S at Gärstadverken.

Appendix A. Model Input Values of Dynamic Uncertainties

A1. Uncertainty Ranges – ETS Prices

Table 15. Input values given the helping function for generation of ETS-price trajectories as shown in Figure 40.

Input to helping funtion	Abbreviation	Scenario	Range	Source
ETS price 2030	*pETS_2030*	*CCT*	770-1430 SEK/t	Based on (Profu p.c. 2024)
		ESF	1430-1650 SEK/t	ibid
		RSF	1650-2000 SEK/t	ibid
ETS plateau price	*pETS_vPlat*	*CCT*	1034-1925 SEK/t	ibid
		ESF	1925-2838 SEK/t	ibid
		RSF	2838-6000 SEK/t	Min. based on (Profu p.c. 2024) and max. on (SEA 2025b)
Year ETS price plateau is reached	*pETS_yP*	*CCT, ESF, RSF*	2050-2060	Assumption
ETS price volatility	*pETS_dt*	*CCT, ESF, RSF*	0.01-0.04	Assumption

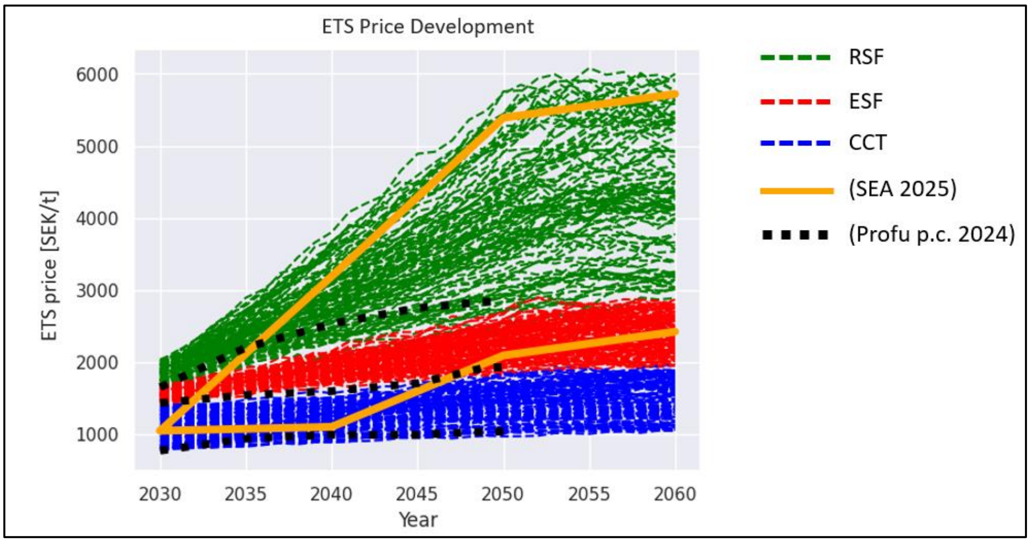


Figure 40. ETS price developments as simulated in Rhodium, as well as predicted price developments presented by Profu (p.c. 2024) and the Swedish Energy Agency (2025b).

A2. Uncertainty Ranges – Electricity Prices

Table 16. Input values given the helping function for the generation of electricity price trajectories as shown in Figure 41.

Input to helping function	Abbreviation	Scenario	Range	Source
Electricity price 2030	*pElec_2030*	*CCT*	464-564 SEK/MWh	Based on (Profu p.c. 2024)
		ESF	770-870 SEK/MWh	Ibid
		RSF	825-925 SEK/MWh	Ibid
Electricity plateau price	*pElec_vPlat*	*CCT*	501-601 SEK/MWh	Ibid
		ESF	583-683 SEK/MWh	Ibid
		RSF	691-791 SEK/MWh	Ibid
Year electricity price plateau is reached	*pElec_yPlat*	*CCT, ESF, RSF*	2035-2050	Assumption
Electricity price volatility	*pElec_dt*	*CCT, ESF, RSF*	0.01-0.04	Assumption

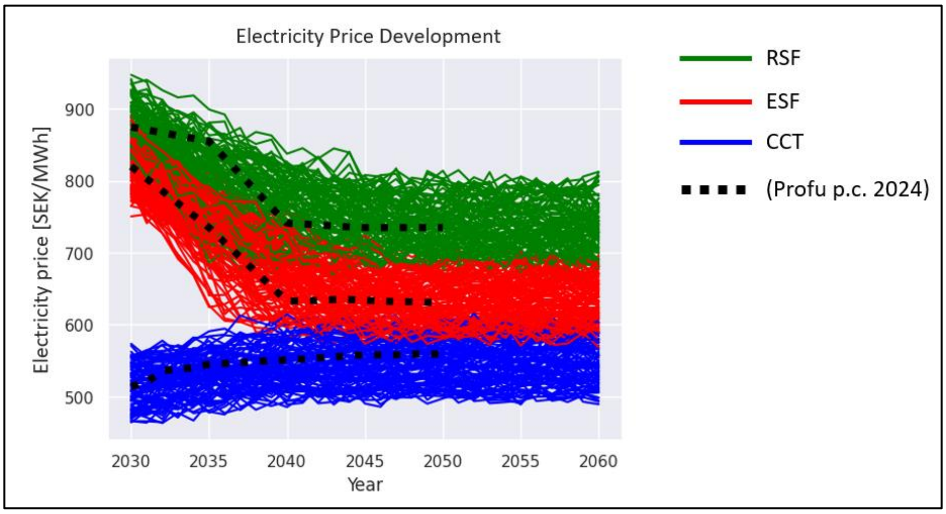


Figure 41. Electricity price developments as simulated in Rhodium, as well as price predictions by Profu (p.c. 2024)

A3. Uncertainty Ranges – Fraction Fossil CO_2

Table 17. Uncertainty ranges of the parameters used to create the trajectories of the fossil fraction of captured CO_2. Examples of trajectories are shown in Figure 42.

Parameter	Abbreviation	Range	Source
Fossil CO_2 captured 2030	*fCO2_2030*	100000 - 137500 tonne (40-55% of total CO_2 captured)	Assumption
Fossil CO_2 captured 2060	*fCO2_2060*	12500 - 187500 tonne (5-75% of total CO_2 captured)	Assumption

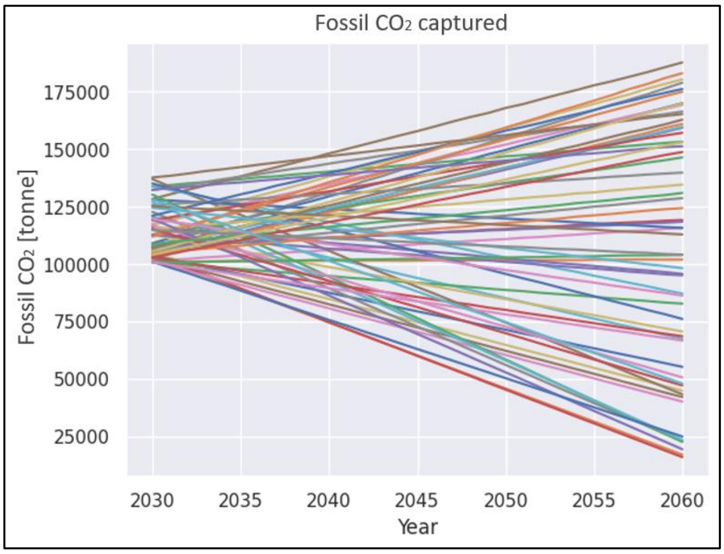


Figure 42. Development of the amount of fossil CO_2 captured as simulated in Rhodium.

A4. Uncertainty Ranges – CAPEX Carbon Capture

Table 18. Uncertainty ranges of the parameters used to create the trajectories of the carbon capture CAPEX. Examples of trajectories are shown in Figure 43.

Parameter	Abbreviation	Range	Source
CC cost 2030	C_0	1400-3000 MSEK	Internal data
CC annual reduction rate	C_{RR}	0.95-1	Assumption

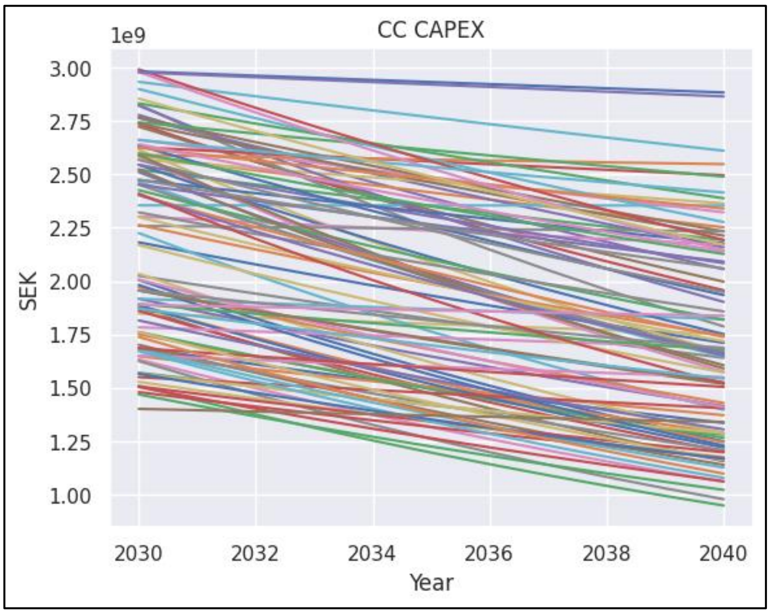


Figure 43. Carbon capture CAPEX trajectories simulated in Rhodium.

A5. Input Values and Uncertainty Ranges – CAPEX Electrolyser

Table 19. Input values related to electrolyser costs. Generated electrolyser cost curves are shown in Figure 44.

Parameter	Abbreviation	Value/Range	Source
Electrolyser cost 2030	E_0	22 MSEK/MW	Internal data
Electrolyser capacity	$C_{H2,MW}$	X MW	Internal data. Assuming 250 000 tonnes of CO_2 are converted into fuel every year.
Electrolyser annual cost reduction	E_{RR}	0.92-1	Assumption (roughly based on results from literature study, see Figure 19a)

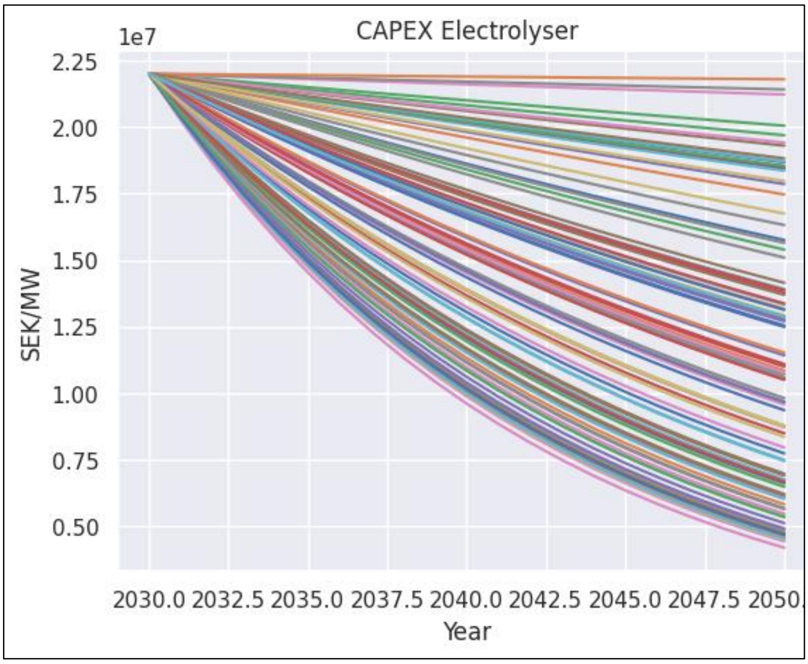


Figure 44. Electrolyser CAPEX trajectories simulated in Rhodium.

Appendix B. Results

B1. Sobol Sensitivity Results

Table 20. Results from CCS Sobol Sensitivity Analysis. Refers to the sensitivity of the Regret of investing in CCS (R_{CCS}) with respect to the uncertain parameters. Includes first-order (S1), second-order (S2), and total-order (ST) sensitivity indices as well as their confidence interval (Conf.) with alpha = 5%.

Sobol Sensitivity Results - CCS							
CCT 2030							
Parameter	**S1**	**Conf.**	**ST**	**Conf.**	**S2 - parameters**	**S2**	**Conf.**
pCRC	0.758084	0.014014	0.793597	0.011737	pCRC - TS	0.013607	0.017708
TS	0.102684	0.004778	0.123134	0.002193	C0 - pCRC	0.011071	0.008157
C0	0.083868	0.004352	0.101225	0.001761	fCO2_2060 - pCRC	0.003383	0.002484
fCO2 2060	0.006574	0.001823	0.01344	0.000349			
pETS 2030	0.005495	0.001275	0.006925	0.000127			
fCO2 2030	0.002605	0.001188	0.005383	0.000149			
pETS vPLAT	0.001979	0.00081	0.002757	0.000052			
pETS yPlat	0.00004	0.000178	0.000148	0.000004			
pElec vPLAT	0	0.000096	0.000028	0.000001			
pElec 2030	0.00005	0.00007	0.000019	0			
pElec yPlat	-0.00001	0.000047	0.000011	0			
CRR	0.000004	0.000051	0.000008	0			
pElec dt	-0.000026	0.000044	0.000008	0			
pETS dt	-0.000035	0.000047	0.000008	0			
CCT 2040							
Parameter	**S1**	**Conf.**	**ST**	**Conf.**	**S2 - parameters**	**S2**	**Conf.**
pCRC	0.724085	0.012225	0.796112	0.01145	pCRC - TS	0.027357	0.016905
TS	0.093905	0.005733	0.133342	0.002732	C0 - pCRC	0.013228	0.007476
C0	0.047789	0.004182	0.071176	0.001572	fCO2_2060 - pCRC	0.012523	0.004328
fCO2 2060	0.015311	0.003319	0.041399	0.001332	CRR- pCRC	0.006046	0.005422
CRR	0.024779	0.003038	0.037358	0.000871	fCO2_2060 - TS	0.002862	0.005075
pETS vPLAT	0.009058	0.001853	0.014772	0.000316	C0 - CRR	0.002556	0.006297
pETS 2030	0.000861	0.000588	0.001506	0.000032	fCO2_2060 - pETS_vPlat	0.002512	0.004853
fCO2 2030	0.000563	0.000586	0.001183	0.000043	pETS_vPlat - pCRC	0.002138	0.003167
pETS yPlat	0.000142	0.000297	0.000451	0.000016			
pElec vPLAT	0.000068	0.000122	0.000069	0.000001			
pElec yPlat	0.000028	0.000053	0.000012	0			
pElec 2030	0.000024	0.000048	0.000011	0			
pElec dt	0.00002	0.000046	0.000011	0			
pETS dt	0.000002	0.000056	0.000011	0			

ESF 2030							
Parameter	**S1**	**Conf.**	**ST**	**Conf.**	**S2 - parameters**	**S2**	**Conf.**
pCRC	0.7557	0.01253	0.812824	0.010761	pCRC - TS	0.025552	0.015851
TS	0.098644	0.00573	0.132719	0.00272	C0 - pCRC	0.021059	0.009561
C0	0.080179	0.00553	0.10912	0.002125	fCO2_2060 - pCRC	0.002952	0.001542
fCO2 2060	0.000755	0.001251	0.006093	0.000196	C0 - TS	0.002753	0.00781
pETS vPLAT	0.002227	0.000847	0.00314	0.000066			
fCO2 2030	0.00049	0.000769	0.002594	0.000086			
pETS 2030	0.000531	0.000456	0.00086	0.000017			
pETS yPlat	0.000281	0.000339	0.000495	0.000011			
pElec yPlat	0.000049	0.000122	0.000054	0.000001			
pElec vPLAT	0.000012	0.000093	0.00004	0.000001			
pElec 2030	0.000017	0.000087	0.00003	0.000001			
CRR	0.000001	0.000067	0.000018	0.000001			
pElec dt	0.000038	0.000067	0.000018	0.000001			
pETS dt	-0.000009	0.000075	0.000018	0			
ESF 2040							
Parameter	**S1**	**Conf.**	**ST**	**Conf.**	**S2 - parameters**	**S2**	**Conf.**
pCRC	0.693803	0.011586	0.819624	0.013901	pCRC - TS	0.055905	0.018357
TS	0.088782	0.006201	0.156267	0.003283	C0 - pCRC	0.026843	0.008447
C0	0.045079	0.004092	0.084794	0.001878	fCO2_2060 - pCRC	0.017082	0.00408
CRR	0.023332	0.003616	0.045202	0.001062	CRR- pCRC	0.013458	0.006571
fCO2_2060	0.000439	0.002227	0.023858	0.000718	pETS_vPlat - pCRC	0.004796	0.004218
pETS_vPlat	0.0083	0.00225	0.017532	0.000433	C0 - CRR	0.003538	0.0072
pETS_yPlat	0.00033	0.000685	0.001599	0.000055	C0 - TS	0.00293	0.006955
fCO2_2030	-0.000111	0.000364	0.000558	0.00002	CRR- TS	0.00253	0.006042
pETS_2030	0.000041	0.000262	0.000225	0.000006			
pElec_vPlat	-0.000028	0.000165	0.0001	0.000003			
pElec_yPlat	-0.00013	0.000112	0.000041	0.000001			
pElec_2030	-0.000057	0.00009	0.000029	0.000001			
pElec_dt	-0.000086	0.000077	0.000029	0.000001			
pETS_dt	-0.000124	0.000096	0.000029	0.000001			
RSF 2030							
Parameter	**S1**	**Conf.**	**ST**	**Conf.**	**S2 - parameters**	**S2**	**Conf.**
pCRC	0.674831024	0.011071	0.799765487	0.013286977	pCRC - TS	0.050504	0.017193
TS	0.089537949	0.0059591	0.153172737	0.003381087	C0 - pCRC	0.041473	0.01092
C0	0.072304855	0.0053339	0.126294335	0.002833585	pETS_vPlat - pCRC	0.012436	0.006028
pETS vPLAT	0.021904045	0.0033762	0.041490144	0.000888188	fCO2_2060 - pCRC	0.007868	0.0038
fCO2 2060	0.003631214	0.001753	0.013428178	0.000443817	C0 - TS	0.003954	0.008016
pETS yPlat	0.002083109	0.0009524	0.004909741	0.000135117			
pETS 2030	0.001426293	0.0008158	0.002498936	5.94565E-05			
fCO2 2030	0.000316556	0.0007804	0.002448541	8.07009E-05			

pElec vPLAT	2.73842E-05	0.0001254	6.90531E-05	1.85301E-06			
pElec yPlat	2.73534E-05	0.0001337	6.62883E-05	1.87294E-06			
pElec 2030	4.52304E-06	0.0001281	5.828E-05	1.89301E-06			
pETS dt	8.62731E-05	0.0001014	4.35436E-05	1.35332E-06			
CRR	-6.55493E-05	0.000117	4.28564E-05	1.34129E-06			
pElec dt	1.43016E-05	0.0001132	4.27425E-05	1.40281E-06			
RSF 2040							
Parameter	**S1**	**Conf.**	**ST**	**Conf.**	**S2 - parameters**	**S2**	**Conf.**
pCRC	0.405869	0.017693	0.764837	0.018693	fCO2_2060 - pCRC	0.101318	0.016031
TS	0.054083	0.006558	0.184048	0.006314	pCRC - TS	0.076656	0.028117
fCO2 2060	0.04273	0.006961	0.182346	0.007021	pETS_vPlat - pCRC	0.068522	0.014283
pETS vPLAT	0.049949	0.007333	0.16661	0.006478	C0 - pCRC	0.037404	0.01154
C0	0.029393	0.004712	0.1051	0.004049	CRR- pCRC	0.020044	0.009009
CRR	0.015042	0.004057	0.057713	0.002193	fCO2_2060 - TS	0.00706	0.011578
pETS yPlat	0.002835	0.001607	0.010815	0.000465	pETS_vPlat - TS	0.005119	0.012556
fCO2 2030	0.000936	0.000964	0.003156	0.000141	C0 - CRR	0.003337	0.008858
pETS 2030	0.000084	0.00036	0.000614	0.000027	CRR- pETS_vPlat	0.003197	0.006981
pElec vPLAT	-0.000014	0.000214	0.000162	0.000007	C0 - pETS_vPlat	0.003132	0.008645
pElec yPlat	0.00005	0.000156	0.00008	0.000004	pETS_yPlat - pCRC	0.002848	0.003792
pETS dt	-0.00002	0.000144	0.000076	0.000004	C0 - TS	0.002746	0.008744
pElec 2030	0.000022	0.000138	0.000075	0.000004	CRR- fCO2_2060	0.002457	0.007086
pElec dt	0.000061	0.000164	0.000072	0.000004	CRR- TS	0.002424	0.007036
					fCO2_2060 - pETS_vPlat	0.002353	0.010218
					TS - CRC	0.002112	0.011123
					C0 - fCO2_2060	0.002072	0.008551

Table 21. Results from CCU Sobol Sensitivity Analysis. Refers to the sensitivity of the Regret of investing in CCU (R_{CCU}) with respect to the uncertain parameters. Includes first-order (S1), second-order (S2), and total-order (ST) sensitivity indices as well as their confidence interval (Conf.) with alpha = 5%.

Sobol Sensitivity Results - CCU							
CCT 2030							
Parameter	**S1**	**Conf.**	**ST**	**Conf.**	**S2 - parameters**	**S2**	**Conf.**
peSAF	0.928575	0.023028	0.983822	0.0139	C0 - peSAF	0.035663	0.008563
C0	0.012659	0.002998	0.050049	0.001745	pElec_vPlat - peSAF	0.00904	0.004407
pElec_vPlat	0.003503	0.001682	0.014654	0.000532	pElec_2030 - peSAF	0.005174	0.003587
pElec_2030	0.001593	0.00138	0.008243	0.000305			
pElec_yPlat	-0.000008	0.000828	0.002146	0.00011			
pETS_dt	-0.000074	0.000202	0.000187	0.000009			
CRR	-0.000175	0.000188	0.000186	0.000009			
fCO2_2030	-0.000176	0.000209	0.000182	0.000008			
fCO2_2060	-0.000194	0.000186	0.000182	0.000008			
pETS_yPlat	-0.000051	0.0002	0.000182	0.000009			
pElec_dt	-0.000133	0.000205	0.000181	0.000008			
ERR	-0.000048	0.000185	0.00018	0.000008			
pETS_2030	-0.000149	0.000193	0.00018	0.000009			
pETS_vPlat	-0.000199	0.000187	0.000179	0.000008			
CCT 2040							
Parameter	**S1**	**Conf.**	**ST**	**Conf.**	**S2 - parameters**	**S2**	**Conf.**
peSAF	0.466761	0.03183	0.920754	0.032118	ERR- peSAF	0.251944	0.035786
ERR	0.042629	0.011017	0.352471	0.019578	pElec_vPlat - peSAF	0.059261	0.016385
pElec_vPlat	0.010309	0.005095	0.106655	0.005684	C0 - peSAF	0.051847	0.013445
C0	0.007099	0.004692	0.097838	0.005683	CRR- peSAF	0.024003	0.012673
CRR	0.007245	0.00403	0.053565	0.003223	C0 - ERR	0.005486	0.008689
pElec_yPlat	-0.000215	0.000974	0.002514	0.000198	ERR- pElec_vPlat	0.004986	0.017302
pElec_2030	0.000144	0.000489	0.001411	0.000113	C0 - pElec_vPlat	0.003848	0.007935
pETS_yPlat	-0.000076	0.000474	0.000661	0.000055	C0 - CRR	0.0031	0.008329
fCO2_2030	-0.000189	0.000481	0.000645	0.000047			
fCO2_2060	-0.00004	0.000383	0.000642	0.000045			
pElec_dt	-0.000286	0.000419	0.000629	0.000046			
pETS_dt	-0.000382	0.000454	0.000627	0.000043			
pETS_2030	-0.000256	0.000439	0.000625	0.000047			
pETS_vPlat	0.000106	0.000397	0.000624	0.000043			
ESF 2030							
Parameter	**S1**	**Conf.**	**ST**	**Conf.**	**S2 - parameters**	**S2**	**Conf.**
peSAF	0.948944	0.013559	0.978827	0.011894	C0 - peSAF	0.013845	0.005899
C0	0.013268	0.002807	0.028051	0.000685	pElec_yPlat - peSAF	0.006705	0.003558
pElec_yPlat	0.005125	0.001749	0.012885	0.000354	pElec_vPlat - peSAF	0.004054	0.002691
pElec_vPlat	0.003005	0.001287	0.008031	0.000214	pElec_2030 - peSAF	0.00203	0.002125
pElec_2030	0.001865	0.000947	0.004846	0.000137			
pETS_yPlat	-0.000068	0.000227	0.000196	0.000006			

ERR	0.00007	0.00021	0.000193	0.000007			
pETS_vPlat	-0.000049	0.00019	0.000193	0.000006			
pETS_2030	0.000256	0.000217	0.000192	0.000006			
fCO2_2060	0.00008	0.000185	0.00019	0.000006			
pETS_dt	0.000215	0.000195	0.00019	0.000007			
CRR	0.000048	0.000219	0.000189	0.000007			
fCO2_2030	0.000013	0.000213	0.000188	0.000007			
pElec_dt	0.00003	0.000215	0.000188	0.000006			
ESF 2040							
Parameter	**S1**	**Conf.**	**ST**	**Conf.**	**S2 - parameters**	**S2**	**Conf.**
peSAF	0.706234	0.02077	0.931945	0.021799	ERR- peSAF	0.127591	0.017445
ERR	0.039865	0.006754	0.182462	0.005917	pElec_vPlat - peSAF	0.033694	0.009379
pElec_vPlat	0.011486	0.003264	0.054011	0.002148	C0 - peSAF	0.02899	0.009548
C0	0.008591	0.003399	0.047611	0.00204	CRR- peSAF	0.012835	0.007004
CRR	0.005149	0.002959	0.025535	0.001013	pElec_yPlat - peSAF	0.004229	0.003889
pElec_yPlat	0.001633	0.00127	0.009475	0.00042	C0 - ERR	0.002482	0.006527
pElec_2030	0.000074	0.000411	0.000808	0.000041	C0 - CRR	0.002105	0.005913
pETS_dt	0.000025	0.00028	0.000414	0.000024			
pETS_yPlat	-0.000073	0.000326	0.000413	0.00002			
fCO2_2060	-0.000013	0.000332	0.000412	0.000022			
pETS_vPlat	-0.000028	0.000336	0.000412	0.000021			
fCO2_2030	-0.000024	0.000298	0.000407	0.000021			
pETS_2030	-0.000052	0.000273	0.0004	0.00002			
pElec_dt	0.000013	0.000296	0.000398	0.00002			
RSF 2030							
Parameter	**S1**	**Conf.**	**ST**	**Conf.**	**S2 - parameters**	**S2**	**Conf.**
peSAF	0.965746	0.013852	0.983303	0.011337	C0 - peSAF	0.011516	0.004648
C0	0.0092	0.002316	0.021223	0.000459	pElec_vPlat - peSAF	0.002787	0.00243
pElec_vPlat	0.002808	0.00127	0.006092	0.000148			
pElec_yPlat	0.002569	0.001146	0.005336	0.000159			
pElec_2030	0.001708	0.000803	0.003625	0.000095			
fCO2_2060	-0.000046	0.000208	0.000178	0.000006			
CRR	0.000234	0.000232	0.000176	0.000005			
pElec_dt	0.000132	0.000204	0.000176	0.000005			
pETS_2030	0.000062	0.000191	0.000176	0.000006			
pETS_vPlat	0.00024	0.000219	0.000176	0.000005			
pETS_dt	0.000152	0.000217	0.000175	0.000005			
ERR	0.00001	0.000195	0.000174	0.000005			
pETS_yPlat	0.000121	0.000199	0.000174	0.000005			
fCO2_2030	0.000116	0.000207	0.000172	0.000006			

RSF 2040							
Parameter	**S1**	**Conf.**	**ST**	**Conf.**	**S2 - parameters**	**S2**	**Conf.**
peSAF	0.837004	0.017817	0.945549	0.014579	ERR- peSAF	0.063198	0.010443
ERR	0.032508	0.005094	0.100305	0.002926	pElec_vPlat - peSAF	0.01702	0.005634
pElec_vPlat	0.009172	0.0025	0.029807	0.000992	C0 - peSAF	0.014433	0.00519
C0	0.008133	0.002282	0.025865	0.000836	CRR- peSAF	0.007428	0.003973
CRR	0.00413	0.00165	0.013568	0.000509			
pElec_yPlat	0.000694	0.000937	0.002924	0.000106			
pElec_2030	0.000237	0.000351	0.000509	0.00002			
fCO2_2060	0.000058	0.000279	0.000297	0.00001			
pETS_2030	0.000128	0.000294	0.000295	0.000013			
pElec_dt	-0.000046	0.000236	0.000294	0.00001			
pETS_vPlat	0.000103	0.000253	0.000289	0.000013			
pETS_dt	0.000036	0.000263	0.000288	0.000011			
fCO2_2030	0.000031	0.000255	0.000286	0.000011			
pETS_yPlat	-0.000025	0.000247	0.000284	0.000012			

B2. CART Results

Table 22. Results from CCS CART analysis where the case of interest is $R_{CCS} = 0$. For description of the accuracy, see section 9.3.1 CART. For parameter units, see section iii. Abbreviations Appearing in Part IV.

CART Results - CCS						
Scenario (accuracy)	**Class**	**Density (%)**	**Coverage (%)**	**Rule(s)**		
CCT 2030 ***(acc: 0.9213)***	$R_{CCS} = 0$	62.3	83.6	pCRC ≥ 3793		
		78.4	66.5	pCRC ≥ 3794	TS ≤ 1600	
		90.4	54.3	pCRC ≥ 3794	TS ≤ 1600	C0 ≤ 2.514e9
		96.5	38.9	pCRC ≥ 3794	TS ≤ 1600	C0 ≤ 2.137e9
	$R_{CCS} > 0$	95.1	86.2	pCRC ≤ 3794		
		99.3	70.4	pCRC ≤ 3152		
		99.8	64.5	pCRC ≤ 2939		
		100.0	58.3	pCRC ≤ 2939	TS ≥ 1142	
CCT 2040 ***(acc: 0.887)***	$R_{CCS} = 0$	74.6	88.6	pCRC ≥ 3276		
		88.9	62.4	pCRC ≥ 3276	fCO2_2060 ≤ 116.9e3	
		95.0	50.1	pCRC ≥ 3276	fCO2_2060 ≤ 116.9e3	TS ≤ 1720
		97.9	43.0	pCRC ≥ 3585	fCO2_2060 ≤ 116.9e3	TS ≤ 1720
	$R_{CCS} > 0$	93.2	83.9	pCRC ≤ 3276		
		97.6	72.7	pCRC ≤ 2843		
		99.7	57.6	pCRC ≤ 2372		
		99.9	55.5	pCRC ≤ 2372	TS ≥ 1086	
ESF 2030 ***(acc: 0.9153)***	$R_{CCS} = 0$	75.7	86.1	pCRC ≥ 3562		
		90.9	59.4	pCRC ≥ 3562	TS ≤ 1576	
		95.4	50.9	pCRC ≥ 3827	TS ≤ 1576	
		97.1	47.2	pCRC ≥ 3827	TS ≤ 1576	C0 ≤ 2.847e9
	$R_{CCS} > 0$	93.6	88.0	pCRC ≤ 3562		
		98.7	69.5	pCRC ≤ 2872		
		99.6	60.5	pCRC ≤ 2872		
		99.9	56.7	pCRC ≤ 2872	C0 ≥ 1.610e9	TS ≥ 1107
ESF 2040 ***(acc: 0.9047)***	$R_{CCS} = 0$	84.8	88.7	pCRC ≥ 2869		
		93.0	73.3	pCRC ≥ 3398		
		97.2	58.6	pCRC ≥ 3398	TS ≤ 1737	
		98.1	54.7	pCRC ≥ 3398	TS ≤ 1737	C0 ≤ 2.877e9
	$R_{CCS} > 0$	88.8	84.9	pCRC ≤ 2869		
		96.1	69.8	pCRC ≤ 2381		
		98.2	59.9	pCRC ≤ 2381	TS ≥ 1193	
		99.5	48.2	pCRC ≤ 2066	TS ≥ 1193	
RSF 2030 ***(acc: 0.91)***	$R_{CCS} = 0$	83.1	88.6	pCRC ≥ 2929		
		92.9	70.3	pCRC ≥ 3535		
		97.3	58.5	pCRC ≥ 3535	TS ≤ 1747	
		99.0	51.2	pCRC ≥ 3535	TS ≤ 1747	C0 ≤ 2.767e9
	$R_{CCS} > 0$	89.4	84.3	pCRC ≤ 2929		
		96.8	63.1	pCRC ≤ 2290		
		99.4	45.3	pCRC ≤ 2290	TS ≥ 1326	
		99.8	41.4	pCRC ≤ 2170	TS ≥ 1326	
RSF 2040 ***(acc: 0.881)***	$R_{CCS} = 0$	93.3	83.9	pCRC ≥ 2211		
		97.2	73.2	pCRC ≥ 2661		
		98.8	61.2	pCRC ≥ 3076		
		99.5	55.6	pCRC ≥ 3076	TS ≤ 1861	
	$R_{CCS} > 0$	63.5	82.4	pCRC ≤ 2211		
		80.9	48.9	pCRC ≤ 2211	pETS_vPlat ≤ 4337	
		91.3	36.5	pCRC ≤ 2211	pETS_vPlat ≤ 4337	TS ≥ 1342

Table 23. Results from CCU CART analysis where the case of interest is $R_{CCU} = 0$. For description of the accuracy, see section 9.3.1 CART. For parameter units, see section iii. Abbreviations Appearing in Part IV.

CART Results - CCU						
Scenario (accuracy)	**Class**	**Density (%)**	**Coverage (%)**	**Rule(s)**		
CCT 2030 ***(acc: 0.9703)***	$R_{CCU} = 0$	98.6	98.1	peSAF > 50.91		
		99.6	95.9	peSAF > 52.19		
		100.0	92.9	peSAF > 53.39		
		100.0	91.1	peSAF > 54.09		
	$R_{CCU} > 0$	93.0	94.7	peSAF <= 50.91		
		99.3	78.8	peSAF <= 48.51		
		100.0	72.6	peSAF <= 47.85		
CCT 2040 ***(acc: 0.9663)***	$R_{CCU} = 0$	98.2	97.0	peSAF > 46.24		
		99.5	93.2	peSAF > 48.51		
		99.9	88.8	peSAF > 50.60		
		100.0	83.8	peSAF > 52.77		
	$R_{CCU} > 0$	78.5	85.8	peSAF <= 46.24		
		91.3	67.8	peSAF <= 46.24	ERR > 0.9450	
		99.2	46.0	peSAF <= 43.82	ERR > 0.9450	
		100.0	33.8	peSAF <= 42.77	ERR > 0.9450	
ESF 2030 ***(acc: 0.9783)***	$R_{CCU} = 0$	97.3	97.8	peSAF > 57.93		
		99.5	93.0	peSAF > 60.26		
		99.9	90.1	peSAF > 61.32		
		100.0	88.0	peSAF > 62.06		
	$R_{CCU} > 0$	96.1	95.1	peSAF <= 57.93		
		99.0	89.0	peSAF <= 56.32		
		99.9	83.1	peSAF <= 55.10		
		100.0	78.8	peSAF <= 55.10	pElec_vPlat > 588.4	
ESF 2040 ***(acc: 0.9677)***	$R_{CCU} = 0$	97.0	98.0	peSAF > 49.27		
		99.2	94.2	peSAF > 51.71		
		99.8	90.5	peSAF > 53.54		
		100.0	86.3	peSAF > 55.24		
	$R_{CCU} > 0$	91.2	87.4	peSAF <= 49.27		
		98.2	68.5	peSAF <= 46.75		
		99.8	62.2	peSAF <= 46.75	ERR > 0.9277	
		100.0	55.0	peSAF <= 46.75	ERR > 0.9277	pElec_yPlat > 2036
RSF 2030 ***(acc: 0.977)***	$R_{CCU} = 0$	97.5	97.5	peSAF > 61.73		
		99.6	93.4	peSAF > 63.51		
		99.9	90.8	peSAF > 64.33		
		100.0	87.6	peSAF > 65.29		
	$R_{CCU} > 0$	96.6	96.7	peSAF <= 61.73		
		99.6	90.4	peSAF <= 59.73		
		100.0	85.0	peSAF <= 58.53		
		100.0	81.7	peSAF <= 58.53	fCO2_2060 > 19640	

RSF 2040 *(acc: 0.965)*	$R_{CCU} = 0$	**97.7**	**96.0**	**peSAF > 54.82**		
		99.3	92.3	peSAF > 56.69		
		100.0	84.3	peSAF > 59.85		
		100.0	81.6	peSAF > 59.85	ERR <= 0.9973	
	$R_{CCU} > 0$	90.0	94.2	peSAF <= 54.82		
		99.3	74.5	peSAF <= 50.59		
		99.8	67.5	peSAF <= 49.59		
		100.0	59.7	peSAF <= 49.59	pElec_vPlat > 703.5	

B3. PRIM Results

Table 24. Results from CCS PRIM analysis. For parameter units, see section iii. Abbreviations Appearing in Part IV.

PRIM Results - CCS				
Scenario	**Case of interest**	**Density and Coverage**	**Rule**	**qp-value**
CCT 2030	$R_{CCS} = 0$	**Density (%)** 90.8654 **Coverage (%)** 46.2103	pCRC >= 3951	0
			TS <= 1643	3.37E-33
			C0 <= 2.472e9	8.30E-22
			fCO2_2060 <= 1.769e5	1.54E-01
	$R_{CCS} > 0$	**Density (%)** 90.7908 **Coverage (%)** 92.9478	pCRC <= 4229	6.72E-167
CCT 2030	$R_{CCS} = 0$	**Density (%)** 90.4572 **Coverage (%)** 59.0211	pCRC >= 3570	0
			fCO2_2060 <= 1.279e5	1.09E-51
	$R_{CCS} > 0$	**Density (%)** 90.046 **Coverage (%)** 86.6351	pCRC <= 3446	0.00E+00
ESF 2030	$R_{CCS} = 0$	**Density (%)** 90.1869 **Coverage (%)** 63.5914	pCRC >= 3718	0
			TS <= 1736	3.21E-25
			C0 <= 2.84e9	4.15E-05
	$R_{CCS} > 0$	**Density (%)** 90.7908 **Coverage (%)** 90.9261	pCRC <= 3732	0.00E+00
ESF 2040	$R_{CCS} = 0$	**Density (%)** 90.7088 **Coverage (%)** 79.4296	pCRC >= 3056	0
			TS <= 1860	1.75E-10
	$R_{CCS} > 0$	**Density (%)** 90.0452 **Coverage (%)** 83.8654	pCRC <= 2846	0.00E+00

RSF 2030	$R_{CCS} = 0$	**Density (%)** **90.9766** **Coverage (%)** **74.2795**	**pCRC >= 3418**	**0.00E+00**
	$R_{CCS} > 0$	**Density (%)** 90.3736 **Coverage (%)** 81.7642	pCRC <= 2846	0.00E+00
RSF 2040	$R_{CCS} = 0$	**Density (%)** 90.1619 **Coverage (%)** 88.3938	pCRC >= 1913	2.19E-240
	$R_{CCS} > 0$	**Density (%)** 90.5936 **Coverage (%)** 39.6166	pCRC <= 2029	3.30E-305
			pETS_vPlat <= 4950	1.98E-16
			fCO2_2060 <= 1.422e5	2.00E-14
			TS >= 1254	4.65E-09

Table 25. Results from CCU PRIM analysis. For parameter units, see section iii. Abbreviations Appearing in Part IV.

PRIM Results - CCU				
Scenario	**Case of interest**	**Density and Coverage**	**Rule**	**qp-value**
CCT 2030	$R_{CCU} = 0$	**Density (%)** 91.2166 **Coverage (%)** 100	**Restricted dimension**	**qp-value**
			pSAF >= 47.13	5.56E-228
	$R_{CCU} > 0$	**Density (%)** 89.629 **Coverage (%)** 97.5229	**Restricted dimension**	**qp-value**
			pSAF <= 51.858	0.00E+00
CCT 2040	$R_{CCU} = 0$	**Density (%)** 93.0842 **Coverage (%)** 99.6956	**Restricted dimension**	**qp-value**
			pSAF >= 42.50	2.52E-47
	$R_{CCU} > 0$	**Density (%)** 90.8136 **Coverage (%)** 61.2389	**Restricted dimension**	**qp-value**
			pSAF <= 45.98	0.00E+00
			ERR >= 0.95	4.54E-22
ESF 2030	$R_{CCU} = 0$	**Density (%)** 90.3166 **Coverage (%)** 99.9366	**Restricted dimension**	**qp-value**
			peSAF >= 55.10	0.00E+00
	$R_{CCU} > 0$	**Density (%)** 91.883 **Coverage (%)** 98.7537	**Restricted dimension**	**qp-value**
			peSAF <= 59.83	0.00E+00
CCT 2040	$R_{CCU} = 0$	**Density (%)** 89.3961 **Coverage (%)** 99.9257	**Restricted dimension**	**qp-value**
			peSAF >=44.88	4.29E-111
	$R_{CCU} > 0$	**Density (%)** 90.8152 **Coverage (%)** 82.1391	**Restricted dimension**	**qp-value**
			peSAF <= 49.17	0.00E+00
			ERR >= 0.924	3.55E-02

RSF 2030	$R_{CCU} = 0$	**Density (%)** **89.8714** **Coverage (%)** **99.8941**	**Restricted dimension**	**qp-value**
			peSAF >= 58.51	0.00E+00
	$R_{CCU} > 0$	**Density (%)** 92.9775 **Coverage (%)** 99.3076	**Restricted dimension**	**qp-value**
			peSAF <= 63.14	0.00E+00
RSF 2040	$R_{CCU} = 0$	**Density (%)** 91.8821 **Coverage (%)** 99.6355	**Restricted dimension**	**qp-value**
			pSAF >= 51.32	0.00E+00
	$R_{CCU} > 0$	**Density (%)** 89.2112 **Coverage (%)** 95.499	**Restricted dimension**	**qp-value**
			peSAF <= 55.34	0.00E+00

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