Towards improved guidelines for cost evaluation of carbon capture and storage

A white paper prepared by

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March 2021

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Acknowledgements

Executive summary

Understanding the costs of carbon capture and storage (CCS) is essential to understand the role for and potential of CCS technology in addressing climate change, for guidance in research activities aiming to reduce the cost and improve the performance of promising new CCS technologies in different applications. In practice, however, there are many challenges in establishing reliable cost estimates for CCS technologies. To help identify and overcome these challenges, a group of experts from industry, government, academia and other organisations came together in 2011 to form the CCS Cost Network (which came under the aegis of IEAGHG in 2017 [1]).

Following discussions at the first CCS Cost Network workshop [1], several members of the workshop steering committee formed a task force to focus on the basic structure of CCS cost estimates. That effort produced a White Paper entitled, "Toward a Common Method of Cost Estimation for CCS at Fossil Fuel Power Plants" [2]. This white paper aimed at overcoming identified pitfalls in CCS cost evaluations for fossil fuel power plants arising from the different methodologies used by various organisations. Towards this aim, the white paper established a common costing methodology and nomenclature, as well as guidelines for CCS cost reporting to improve the clarity and consistency of cost estimates for greenhouse gas mitigation measures.

While that work laid the foundation for establishing a common costing methodology for CCS, several important cost issues still remained to be addressed. Building on that earlier work and the interest from additional organisations, the current white paper is an effort to draw up a complementary set of CCS costing guidelines in three complementary areas where further guidelines and better practices are needed, and where efforts are underway to address those topics. This effort is a collaboration among researchers at several industrial research institutes (Electric Power Research Institute, SINTEF Energy Research), universities (Carnegie Mellon University, Delft University of Technology, Heriot-Watt University, KTH Royal Institute of Technology, NTNU, University of Calgary), governmental laboratories (NETL), intergovernmental organisation (IEA), and international organisation (IEAGHG).

The first area of study tackles the establishment of improved guidelines for cost evaluation of advanced low-carbon technology (such as a new CO_2 capture process or a novel power plant design). While emerging technologies may have the potential to reduce the future cost of CO_2 capture, most techno-economic assessments of emerging technologies are performed considering them as mature. This bias introduces significant challenges to the reliable comparison of technologies at different stages of development, or with different concepts of a particular technology. To address this issue, we develop a framework for estimating the future N^{th}-of-a-kind (NOAK) cost of advanced low-carbon technologies that are currently at early pre-commercial stages of development. This framework addresses the two types of questions that commonly motivate a cost analysis (called "What If" and "What Will" questions). In addition, we address shortcomings in the classic "bottom-up" engineering-economic method currently used to estimate NOAK costs. We further describe a hybrid costing method that combines a bottom-up analysis of the first-of-a-kind (FOAK) commercial cost of an advanced technology with an empirical model employing experience curves to project its future cost.

The second area of study focuses on CCS from non-power industries (such as cement plants, steel mills, refineries, and other industrial sources of CO_2 emissions), which is a growing area of focus for CCS implementation. There are key challenges and factors that are unique to this sector and have a large impact on the cost evaluations of CCS from such facilities but are often overlooked or insufficiently addressed. These include cost metrics (especially in the context of industrial plants

with multiple output products), energy supply aspects, retrofitting costs, maturity of the capture technology, and CO_2 transport and storage cost. We thus seek to develop a set of recommendations to better include and treat these aspects in cost evaluation of CCS in industrial applications. Where possible, examples are given to demonstrate quantitative impact and show how costs may vary widely on a case-by-case basis.

The final area addresses quality assurance and uncertainty evaluations of data and models used in CCS cost analysis. Quantifying the effect of such uncertainties on techno-economic analyses of CCS technologies and systems is critical for proper interpretation and communication of results. As many CCS technologies are novel concepts in early stages of development, substantial uncertainties exist in their performance and cost. Although uncertainty analysis itself is not novel, with some additional methods already frequently used by the CCS techno-economic analysis community, a document that provides a comprehensive overview of methods and approaches, as well as guidance on their selection and use, was still lacking. Given its importance, we seek to fill this gap by providing a critical review of uncertainty analysis methods along with guidance on the selection and use of these methods for CCS techno-economic analyses, highlighting good practice and examples from the CCS literature.

This white paper presents a new set of guidelines developed to address important cost issues in each of these three areas. The paper is organised into three chapters each tackling one of these areas: Chapter 1: Towards improved cost guidelines for advanced low-carbon technologies; Chapter 2: Towards improved cost evaluation of carbon capture and storage from industry; Chapter 3: Toward improved guidelines for uncertainty analysis of carbon capture and storage techno-economic studies. While more detail can be found in each chapter and the corresponding published papers [3-5], a summary is provided below for each topic.

Towards improved cost guidelines for advanced low-carbon technologies

This chapter presents a framework for estimating the future "N^{th}-of-a-kind" (NOAK) cost of advanced technologies that are currently at early pre-commercial stages of development. That framework distinguishes between two types of question that commonly motivate such a cost analysis: "What If" questions about the hypothetical cost of a technology that meets specified R&D goals; and "What Will" questions regarding the actual expected cost of an advanced technology once it is mature.

The latter type of question is of particular interest because of the shortcomings in current methods for estimating the expected NOAK cost that are identified, as well as the ambiguity in many cost studies as to the meaning of reported NOAK costs. Indeed, the first conclusion drawn from this study is that there is a need for greater clarity as to the question a reported NOAK cost result is intended to answer. Going forward, we recommend that authors of cost studies use the term "NOAK goal" or "aspirational NOAK" when conducting "What If" studies, and the term "expected NOAK" or "projected NOAK" when reporting "What Will" estimates of the future cost of an advanced (pre-commercial) technology. While some authors may prefer to use other adjectives to describe study goals, the term NOAK should not be used in isolation without a clear descriptor.

Regarding "What Will" cost estimates for advanced technologies, a hybrid costing method, which combines a "bottom-up" engineering-economic analysis with a "top-down" model of technological learning, offers an approach to address the identified deficiencies in current methods.

The hybrid cost analysis focuses new attention on the current (first-of-a-kind) commercial cost of an advanced technology. Methods and assumptions for estimating FOAK plant costs, which vary significantly from those for known commercial technologies are discussed. A bottom-up FOAK cost estimate is recommended as the starting point for projecting future cost reductions of advanced technologies based on historical experience with similar or related technologies. This is embodied in the application of technology experience curves and historical learning rates that underscore the importance of cumulative experience in plant deployments and operation (together with other factors) in achieving future cost reductions. Methods for implementing these cost models are also elaborated and illustrated. Additional discussions also provide guidelines for the selection of appropriate values of performance and cost parameters for "What If" studies of aspirational NOAK costs for advanced technologies.

As with traditional cost analyses, a variety of tools and methods are available to also characterize uncertainties in cost results and the influence of key decision variables. Three methods, sensitivity analysis, probabilistic analysis, and expert judgments, are discussed and illustrated. An uncertainty analysis is especially important for FOAK and projected NOAK costs for advanced technologies because of their intrinsically greater uncertainty compared to well-established commercial technologies. Uncertainty analysis also is important in calculating aspirational NOAK cost goals since these also depend heavily on assumptions and judgments that may vary considerably.

This chapter represents an initial effort to identify needed improvements in current costing methods and to provide guidance for future cost studies, especially for advanced (pre-commercial) technologies. Continuing efforts also are needed to further develop the models, databases, and guidelines that support applications of the hybrid costing method. This includes methodological improvements and quantitative guidelines to improve the development of FOAK cost estimates and reduce the uncertainties in projected NOAK costs for advanced technologies. Despite current limitations, however, the hybrid modelling approach can enhance prevailing assessments of advanced technologies by providing new insights regarding the time frame and requirements for their cost-competitiveness with existing or other advanced technology concepts. Further applications of the hybrid method can thus begin to offer a more complete and realistic approach to assessing the economic potential of advanced energy, industrial and environmental systems, and priorities for R&D management.

Towards improved cost evaluation of carbon capture and storage from industry

While extensive studies have investigated the techno-economic performance of CCS applied to industrial sources, wide differences in cost estimates have been observed. While this is due in part to differences in the cases studied and the choice of capture technology, a significant part arises from aspects related to cost assessment methods and assumptions. Building on a previous CCS costing guideline paper [6], this chapter aims to contribute to the development of improved guidelines for cost evaluation of CCS from industrial applications. The following key messages and recommendations can be extracted from the work:

- Several publicly available, transparent, and detailed techno-economic studies exist for different industrial sectors (e.g. iron and steel, cement, refinery, hydrogen, ammonia/urea and methanol, pulp and paper). These studies provide a high level of technical and cost details on the industrial facilities considered, which can be used to strengthen future evaluation of CCS from such facilities. Furthermore, these studies have also performed detailed evaluations of currently available CO_2 capture technologies, which can be used as a base case in comparative

assessments involving new technologies. However, it is worth noting that most of these detailed studies are based on European locations and that some industry sectors are not yet studied in sufficient detail and where more specific benchmarks need to be developed in the coming years (e.g. waste-to-energy, offshore oil and gas production facilities, petrochemicals and others).

- The same basic cost metrics used for CCS from power plants are relevant to industrial processes, although in some cases these may be calculated differently. Furthermore, a key challenge that might arise in the calculation of cost metrics for industrial plants is that many processes result in multiple products. In such cases, the cost of CCS may need to be allocated across these products when reporting costs on a normalised basis (e.g., cost per unit of product). While different allocation approaches exist to distribute these (or other) costs, which differentiate between joint and separable costs and between products and by-products, there is no standardised methodology currently in use. Thus, it is recommended to report CCS costs using more than one allocation method as this will provide insights into the impact of different methods on cost performance.

- The origin and production/supply strategy of the steam and electricity required for the CO_2 capture process may vary considerably on a case-by-case basis, and thus have a significant impact on overall cost, associated CO_2 emissions, and the CO_2 avoidance cost. It is recommended that transparent scenarios of realistic (future) heat and power supply strategies be included in cost evaluations and that costing methods and assumptions be explicitly reported. Although this recommendation seems straightforward, it is not common to find cost assessments in literature with high level of transparency, both in assumptions and data.

- The energy supply strategy and the cost and associated emissions intensity of heat and power supplies can also be site-specific and depends on parameters such as energy prices, which can change significantly over time. To understand the impact of these uncertainties, analysts are encouraged to use scenarios for plausible combinations of future energy and carbon prices, so as to clearly understand the impact of possible outcomes.

- To date, few studies properly account for the cost of retrofitting CO_2 capture at existing facilities. As illustrated in the literature, these costs can vary considerably on a case-by-case basis. Thus, retrofit costs and assumptions should be properly accounted for and documented in studies considering retrofit applications of CCS from industry. Particular attention should be paid to the following aspects: economic impact of potentially required plant production stoppages, impacts on the main output product quality and plant operation, flue gas treatment requirements, spatial constraints in plant sites, flue gas interconnection, and utilities connection costs.

- Costs associated with CO_2 transport and storage are often assumed to be a fixed unit cost per tonne of CO_2, independent of the expected transport and storage conditions (distance, volume, and type of transport and storage). While there is significant room to improve the quality of transport and storage cost estimates, it is recommended that any such estimates be based on at least the applicable CO_2 flowrate, type of transport, transport distance and type of storage. Illustrative literature values are provided to support such preliminary estimates when detailed evaluations are not possible. It is worth noting that these considerations hold for CCS at both industrial processes and power plants.

- Technology maturity is an important factor in cost estimates, usually accounted for through the inclusion of process contingency costs for different levels of maturity and experience.

Caution must be taken, however, when considering transferability of technology maturity from power sector applications to various industrial sectors. Impacts to consider include potential effects of CCS on product quality, plant maintenance, and operation of the CCS system under the specific conditions of the industrial facility.

Finally, we strongly recommend that future studies of industrial CCS applications make efforts to better document the adopted costing methodology, assumptions, and data sources, and to incorporate comprehensive uncertainty analyses and scenarios for key assumptions to increase the usefulness and robustness of cost estimates.

Toward improved guidelines for uncertainty analysis of carbon capture and storage techno-economic studies

This chapter reviews and provides guidance on available and emerging methods for uncertainty analysis in CCS techno-economic studies. It is intended to help accelerate continued methods development and their application to more robust and meaningful CCS performance and costing studies, as well as to provide an essential resource for all those developing, communicating, and using CCS costing studies.

We start by outlining the landscape of techno-economic modelling studies - from simplified to very rigorous and detailed, and studies that fall in between these extremes - and discusses the different purposes of uncertainty analysis. These include answering "what will" or "what if" kind of questions, model testing, or factor prioritization. It continues to describe existing uncertainty analysis methods: from local - ranging from 'one-at-a-time' to 'N-ways sensitivity analysis' - to global, e.g., using Monte Carlo Simulation, and provides examples of these from the CCS literature. These methods are described following the "what, how, and when" structure, providing guidance on the use of such methods, and when they come to use and when better not.

The guidelines then review recently developed methods such as pedigree analysis, the pseudo-statistical approach, or the use of surrogate models for global uncertainty analysis of integrated techno-economic models, when the technical models are too computationally heavy to run. These discussions lead to a guidance matrix and decision scheme for selecting uncertainty analysis methods and approaches for specific purposes, technology readiness levels (TRLs) and model types. These guidelines will also help the researchers and technology developers to critically analyse the techno-economic performance of the CCS technology under consideration.

Opportunities that can be achieved through advanced use of uncertainty analyses, such as design of experiments for CCS pilots or design of CCS chains under uncertainty are also discussed. Finally, we highlight the (un)availability of uncertainty analysis options in current flowsheeting software (such as Aspen Plus, gProms, HYSYS) and discusses other software that can be used for undertaking uncertainty analysis.

The key messages from the chapter can be summarized as follows:

- Proper use of uncertainty analysis in the performance of CCS techno-economic analyses can provide more robust understandings of technical and cost performance to modelling practitioners as well as policy- and decision-makers.
- The key to starting any uncertainty analysis is to first define its purpose thoroughly, and then to ensure that the most suitable type of uncertainty analysis for that purpose is selected. The

choice also depends on the existing knowledge of the investigated technology and the associated techno-economic model and its inputs.

- Although most often so-called one-at-a-time sensitivity analysis is applied, the utility of this method is limited to techno-economic analysis, since most techno-economic analyses include non-linearities and parameter interactions. Therefore, a better practice is to use one-way or N-ways sensitivity analysis if probability cannot be quantified in a credible way, and probabilistic uncertainty analysis if probability can be quantified. The latter is best suited to answer prognostic questions, but its utility depends on if credible probability density functions can be assigned to input parameters.

- Ideally, quantitative uncertainty analysis is complemented with qualitative uncertainty methods because they provide insights into the kinds of uncertainty that are unquantifiable, especially relevant to policy and decision making. Note that contrary to popular belief, much uncertainty resides in areas that are not quantifiable. This leaves parts of the total mass of uncertainties not investigated and communicated, providing an incomplete impression of the reliability, quality and accuracy of models and their results.

- Further expanding the capabilities of process simulation software to include advanced global uncertainty approaches would be very helpful, as most software, to our knowledge, do not (except gProms).

- There exists open-source, comprehensive, advanced uncertainty analysis toolboxes, but these require some skill in programming, perhaps providing a barrier for some techno-economic analysis practitioners. Therefore, further improvement of the user-friendliness of these toolboxes (e.g., by including graphic user interfaces) would aid in the wide adoption of advanced uncertainty analysis methods.

Table of contents

11

Abbreviations

AACE	Association for the Advancement of Cost Engineering	GJ	Gigajoule
ADT	Air-dried ton	GTCC	Gas turbine combined cycle
ANN	Artificial neural network	GW, GWe	Gigawatt electric
AP	Air pollution	GWh	Gigawatt-hour
B&V	Black & Veatch	GWh_{cap}	Gigawatt-hour installed capacity
BEC	Bare erected cost	H_2	Hydrogen
BEV	Battery electric vehicle	HEV	Hybrid electric vehicle
BOP	Balance of plant	HHV	Higher heating value
BOS	Balance of system	HRC	Hot-rolled coil
BP	By-product	IEA	International energy agency
BSP	Bleached softwood pulp	IEAGHG	International Energy Agency Greenhouse Gas R&D Programme
Btu	British thermal unit		
CAC	CO_2 avoidance cost		
CAPEX	Capital expenditure	IECM	Integrated Environmental Control Model
CCS	CO_2 capture and storage		
CDF	Cumulative distribution function	IGCC	Integrated gasification combined cycle
CF	Capacity factor		
CHP	Combined heat and power plant	IGFC	Integrated coal gasification fuel cell
CO_2	Carbon dioxide	kg	Kilogram
COE	Cost of electricity	kJ	Kilojoule
CSP	Concentrated solar power	kPa	Kilopascal
DeSOx	Desulphurisation	KPI	Key performance indicator
DOE	Department of Energy	kW	Kilowatt
EBTF	European benchmarking taskforce	kWh	Kilowatt-hour
EDDiCCUT	Environmental due diligence of CO_2 capture and utilisation technologies	LCOE	Levelised cost of electricity
		LCOP	Levelised cost of product
		LCOKM	Levelised cost of key material
		LH	Latin hypercube
EIA	Energy Information Administration	LK	Lime kiln
EPC	Engineering, procurement, and construction	LNG	Liquefied natural gas
		LR	Learning rate
EPRI	Electric Power Research Institute	m^2	Square meter
ESP	Electrostatic precipitator	m^3	Cubic meter
FCEV	Fuel cell electric vehicle	MARS	Multivariate adaptive regression splines
FCF	Fixed charge factor		
FF	Factor fixing, or Fractional factorial	MCMC	Monte Carlo Markov chain
FGD	Flue gas desulphurisation	MCS	Monte Carlo simulation
FOAK	First-of-a-kind	MEA	Monoethanolamine
FP	Factor prioritisation	MFB	Multi-fuel boiler
ft^3	Cubic feet	MP	Main product
GEP	General Electric Power	MPa	Megapascal
GHG	Greenhouse gas	Mt	Million metric tons

MW	Megawatt		TEA	Technoeconomic analysis
MWh	Megawatt-hour		TOC	Total overnight cost
NAT	N-at-a-time (sensitivity analysis)		t, tonne	Metric ton
NEMS	National Energy Modeling System		TPC	Total plant cost
NETL	National Energy Technology Laboratory		TRL	Technology Readiness Level
NCC	National carbon capture center		TS&M	Transport, storage, and monitoring
NGCC	Natural gas combined cycle		U.S.	United States
NGO	Non-governmental organisation		UKM	Unit of key material
NOAK	N^{th}-of-a-kind		UL	Underwriter's Laboratory
NPV	Net present value		UQ	Uncertainty quantification
O&M	Operating and maintenance		UV	Uncertain variable
OAT	One-at-a-time (sensitivity analysis)		WGS	Water gas shift
OPEX	Operational expenditure		wt %	Weight percent
P	Pressure		y, yr	Year
PC	Pulverized coal		ZEP	Zero Emissions Platform
PCE	Polynomial chaos expansion		€	Euro
PDF	Probability distribution function		$/kW	Dollars per kilowatt
PEFC	Polymer electrolyte fuel cell		$/kWh	Dollars per kilowatt-hour
PFC	Process facilities cost		$/MWh	Dollars per megawatt-hour
PR	Progress ratio		°K	Degrees Kelvin
PSA	Pressure swing adsorption			
PSUADE	Problem solving environment for uncertainty analysis and design exploration			
PV	Photovoltaic			
QGESS	Quality Guidelines for Energy System Studies			
R&D	Research and development			
RD&D	Research, development, and demonstration			
REC	Recovery boiler			
ROM	Reduced order model			
R&D	Research and development			
SA	Sensitivity analysis, or System area			
SCPC	Supercritical pulverized coal			
SCR	Selective catalytic reduction			
SDoE	Sequential design of experiments			
SMR	Steam methane reforming			
SO_2	Sulphur dioxide			
SOFC	Solid oxide fuel cell			
SEWGS	Sorption-enhanced water-gas shift			
SRL	System readiness level			
T	Temperature			
T&S	Transport and storage			
TASC	Total as-spent cost			
TCM	Technology centre Mongstad			
tCO_2	Tonne CO_2			

Nomenclature

α	Specific cost at unit cumulative capacity and unit knowledge stock
a	Capital cost per unit for the first (or initial) unit of capacity (Chapter 1)
a	Amount of sampled points in addition to its extremes and the base case (Chapter 3)
b	Learning rate exponent
b_{lbd}	"Learning-by-doing" parameter
b_{lbr}	"Learning-by-researching" parameter
C	Computational cost
E	Expected value
$\hat{g}$	Reduced order model
$I_{CCS,a}$	Annualised investment cost of CCS implementation
k	Number of varied input parameters
$(LCOKM)_{ccs}$	Levelised cost of the key material(s) of the industrial plant with CCS
$(LCOKM)_{ref}$	Levelised cost of the key material(s) of the industrial plant without CCS
LR	Learning rate
m	Model output
n	Model input
$\dot{M}_{CO2,avoided}$	Annual reduction in CO_2 emissions due to CCS for a plant producing the same amount of product(s) with and without CCS
$\dot{M}_{CO2,avoided,i}$	Mass of CO_2 avoided by CCS implementation in year i.
NPV_{CCS}	Annual operating cost of the CCS facility
O_{CCS}	Net present value of total annual CCS costs (which may vary from year to year)
$\mathbb{P}$	Probability
p_i	Preference for choice i
PR	Progress ratio
$(t_{CO2}/U_{Km})_{CCS}$	Mass amount of CO_2 emitted per unit of key material(s) with CCS
$(t_{CO2}/U_{Km})_{ref}$	Mass amount of CO_2 emitted per unit of key material(s) without CCS
U	Uniform distribution
$\mathbf{v}$	Vector of deterministic input parameters
x	Ratio of cumulative to initial capacity of the technology
y	Capital cost per unit for the xth unit of plant capacity
$\boldsymbol{\theta}$	Set of stochastic input parameters

Chapter 1: Towards improved cost guidelines for advanced low-carbon technologies[1]

1.1 Introduction

Research and development (R&D) programs on energy technologies and other industrial processes seek improved, lower-cost systems for producing electricity, fuels, chemicals, and other desired products that reduce environmental emissions of greenhouse gases and other pollutants. Lower-cost technologies for carbon capture and storage (CCS), as well as cleaner, more efficient industrial processes, power plants, and other energy conversion systems, are among the advanced technologies being pursued by researchers worldwide. This chapter is aimed at the wide variety of audiences and stakeholders in the public and private sectors who generate or use cost estimates for such technologies to make or inform decisions regarding R&D programs, investments, policy options, or communications about the outlook for advanced CCS and other low-carbon technologies.

1.1.1 Purpose and scope of this chapter

To assess the viability and competitiveness of a new technology, a common figure of merit is the future cost of a commercial-scale installation once the technology is mature and widely deployed. This cost is commonly referred to as the "N^{th}-of-a-kind" (NOAK) plant cost. Such costs may be sought for a single technology (such as an advanced carbon capture process) as well as for an integrated plant or system employing one or more advanced technology components or novel process integration schemes. At present, however, methods and assumptions for estimating NOAK costs vary widely, resulting in reported NOAK costs that are often ambiguous (at best) or misleading (at worst). This chapter seeks to improve the clarity, consistency, and utility of NOAK cost estimates for advanced technologies by first discussing the purposes of such estimates and then the methods appropriate for different objectives. **The guidance in this chapter is directed mainly at preliminary cost studies conducted in the early stages of a potential project for purposes of scoping and initial feasibility assessments** (in contrast to the far more detailed and costly Front-End Engineering and Design studies used to support final investment decisions). While originally motivated by a focus on advanced carbon capture processes, the methodological issues and approaches to cost estimation discussed in this chapter also apply to a broader array of low-carbon technologies of interest for power generation and other industrial processes.

Throughout this chapter, **the term "advanced" refers to any technology or concept that is still in an early (pre-commercial) stage of development, including technologies that are sometimes referred to as novel, emerging, step-out, breakthrough, game-changing, leapfrog, transformational, next-generation, or other similar terms.** On the nine-point Technology Readiness Level (TRL) scale [7] the technologies of interest in this chapter primarily encompass TRL values from about 3 to 7, which is the major focus of current R&D programs.[2]

The remainder of this section discusses the objectives and questions that motivate a cost analysis of an advanced technology. Clarity of objectives is shown to be essential for choosing an appropriate costing

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[1] This chapter was authored by Edward S. Rubin, Niels Berghout, George Booras, Tim Fout, Monica Garcia, Shareq Mohd Nazir, Andrea Ramirez, Simon Roussanaly, and Mijndert Van der Spek. It builds on the paper, "Rubin, Improving cost estimates for advanced low-carbon power plants," International Journal of Greenhouse Gas Control 88, 1-9. 2019" available at https://doi.org/10.1016/j.ijggc.2019.05.019. The corresponding author for this chapter is Edward S. Rubin (e-mail address: rubin@cmu.edu).

[2] The methods described in this chapter also would apply to the smaller number of advanced technologies that reach TRL 8 or 9. For conceptual designs at TRLs 1 or 2 a detailed cost evaluation is generally not recommended (e.g., see [8])

method. Section 1.2 then presents an overview of the two primary costing methods used for energy technologies: the engineering-economic ("bottom-up") method and the experience curve method. A hybrid method combining these two approaches is introduced as an improved approach to forecast the NOAK costs of advanced technologies for purposes of preliminary assessments.

Sections 1.3 and 1.4 discuss in more detail the use of the engineering-economic method to address the two types of questions that commonly motivate a cost analysis. Here, a distinction is made between the use of a bottom-up costing method for mature technologies (Section 1.3) versus its use for projects employing advanced technology components (Section 1.4). Section 1.5 then describes the use of the hybrid approach to estimate the expected NOAK cost of an advanced technology. Section 1.6 highlights the importance and methods of uncertainty analyses for all cost estimates. Section 1.7 presents an illustrative application of the hybrid costing method. Section 1.8 then concludes with a summary discussion and conclusions.

1.1.1.1 Defining objectives for advanced technology cost estimates

To help identify the most promising advanced technology options, techno-economic studies are regularly carried out by researchers and technology developers in industry, government, and academia. Individuals and organisations also regularly publish cost estimates for advanced technologies. In general, the objective of such cost estimates is to assess the economic viability or competitiveness of an advanced technology relative to an existing current technology. In some cases, comparisons with other advanced technologies also are sought. Such estimates are used by technology developers and researchers to quantify the potential benefits of a new technology relative to a current or competing technology, or a cost reduction goal.

In most cases, advanced technology cost estimates represent the NOAK cost that could be achieved with sufficient replication and maturity if all design goals are met. Towards that end, the most common costing method is a detailed bottom-up engineering-economic approach in which plant and process designs are first specified together with appropriate performance and operating parameters needed to determine all mass and energy flows for the specified system. Based on this information, the cost of purchasing and installing all plant equipment is then estimated for a particular geographic location. This cost is then aggregated with other capital cost elements to obtain the total capital required to construct the overall process or plant (which is often assumed to be at a generic location in a given country). This capital cost is then combined with estimates of annual operating and maintenance (O&M) costs to obtain the total annualized cost of the facility and the cost per unit of product (e.g., per megawatt-hour of electricity in the case of a power plant) for specified financing terms and plant lifetime (for details of these cost calculations and related nomenclature see e.g., [6]).

A similar bottom-up cost analysis is then used to calculate the performance and cost of a reference plant or process, typically a plant employing current (baseline) technology. Differences between the reference plant and the advanced technology plant are used to quantify the economic and performance benefits of the advanced technology. In many cases, the advanced plant design is identical to the reference plant except for a new technology, such as a novel system for post-combustion CO_2 capture and storage.

While the approach outlined above may at first glance appear appropriate for evaluating the future (NOAK) economic competitiveness of an advanced technology, a closer look reveals a methodological flaw for analyses seeking to estimate the likely future cost of a new technology. This can be seen by examining in more detail the types of questions that motivate advanced technology cost estimates.

1.1.2 Motivating questions for cost estimates

To evaluate appropriate costing methods for advanced technologies it is important to first carefully frame the questions that motivate the cost analysis. A review of recent studies [9] indicates that most questions fall into two general categories, referred to in this chapter as Type 1 ("What If") and Type 2 ("What Will") questions.

1.1.2.1 Type 1 questions: What If?

This category of questions arises largely from the R&D community. This group is concerned with issues such as setting targets for R&D programs, identifying the best options to meet technology cost and/or performance goals, and quantifying the expected cost reductions of a successful R&D effort. Accordingly, this group asks questions such as "What R&D goals are needed to achieve a desired cost target for a particular technology or advanced power system?" Conversely, "***What*** would be the cost (or cost reduction) of an advanced technology ***if*** it successfully achieves specified R&D goals?"

This class of questions—which includes a number of variants—characterizes the objective of most cost studies carried out by DOE/NETL and others for advanced energy and environmental technologies. Such studies assume a commercial plant design that meets specified R&D performance goals and component cost targets for the advanced process or system, such as a novel carbon capture process or an advanced power plant design employing several advanced components (e.g. [10-12]). In some cases, R&D goals and targets may reflect extrapolations from bench-scale data or the use of commercial analogies to a novel technology.

In all cases, however, a what-if analysis is a hypothetical construct for a specified process design and a specified set of performance and cost assumptions—typically for an integrated plant with one or more unique (advanced) technology components. Based on these assumptions, a bottom-up engineering-economic analysis is commonly employed to calculate its cost—often referred to as the "NOAK cost."

However, **a bottom-up cost estimate of this kind does not represent the actual expected cost of the technology at some future time since one does not know whether or when the assumed cost and performance targets can actually be achieved** (either in general, or at a specific location)**.** Rather, it is an estimate of the potential cost of an advanced technology for the optimistic case in which all R&D goals and assumptions are realized at some point in the future. Thus, **it is better described as an "aspirational NOAK cost" or "NOAK cost goal."** Note that generally there is no specific timeframe inherent in this type of analysis.

Two common variants of the "What If" questions above are to ask, "What would it take for an advanced technology or system to be competitive with a current baseline system?" or, "How much cheaper would Technology X be compared to Technology Y if its performance and cost goals are met?" In this approach, the performance and cost of all conventional plant components are first established using baseline data, leaving a cost gap or target that the advanced technology must meet in order to be competitive. This approach to costing is discussed in more detail by Guandalini, et al. [13]. In other cases, a scenario analysis or a simple sensitivity analysis is used to identify the conditions (parameter values) under which an advanced technology becomes attractive. Professional judgments also may be applied to assess whether such conditions appear feasible or plausible for these hypothetical outcomes.

1.1.2.2 Type 2 questions: What Will?

A second category of questions is motivated largely by the investment, user, and energy modelling communities (including policy analysts). These groups are interested in the future cost of new technologies at given points in time, and in the cost-competitiveness of an advanced technology relative to existing systems or other competing options. Questions here include: "***What will*** be the likely cost of advanced Technology *X* in future year *Y*? When will the cost of Technology X fall below some specified level (or below the cost of a competing technology)?" and, "***What will*** be the NOAK cost of Technology *X*?" **This can be described as the "expected NOAK cost" or "projected NOAK cost."**

Current methods to address this class of "What Will" question also commonly employ a bottom-up (engineering-economic) analysis of a proposed process and plant design that incorporates the advanced technology of interest. The resulting cost estimate also is typically reported simply as the NOAK cost of the advanced system. However, **many cost studies fail to clearly say whether the reported NOAK cost is intended to represent the actual expected cost of a mature plant (i.e., the answer to a what-will question), or whether it represents only a hypothetical (or aspirational) what-if case**. Absent that

distinction, the implication left in many studies is that the NOAK cost based on a bottom-up estimate indeed represents an expected future cost. In other cases, the meaning of an NOAK cost remains ambiguous.

Later in this chapter, **in Section 1.8, we recommend adoption of the nomenclature highlighted above to distinguish between NOAK cost estimates motivated by the two types of questions.**

1.1.3 Different questions require different costing methods

The key flaw with the common bottom-up approach to what-will cost estimates is that **an engineering-economic cost analysis is simply not appropriate or intended for estimating the actual future NOAK cost of an advanced technology that is not yet commercial.** By definition, the only way to know the true NOAK plant cost is by building N plants. Similarly, the only way to reliably *estimate* the cost of the Nth plant using a bottom-up analysis is by first having built and operated many plants (ideally, $N–1$) of a similar design.

Thus, one cannot correctly claim or suggest that a bottom-up cost estimate for a technology that has never been built and operated at scale represents the true future design and cost of that system, were it to be deployed many (N) times at a commercial scale. Rather, experience shows that technology designs and process flowsheets evolve and change over time as successful technologies mature and become more widely deployed—a process that typically takes several decades or more for large-scale energy technologies. In that dynamic, the capital and operating costs of new system components also change considerably over time, as detailed case studies have shown (e.g., [14]). Thus, one cannot confidently know today what the design and other attributes of a future successful technology will be. One can only hypothesize about future designs, which is inherently a what-if rather than a what-will type of analysis.

For this reason, **different costing methods for advanced technologies are needed to address the two types of questions posed above.** The following section presents an overview of the methods applicable to each type of question. Subsequent sections of this chapter then present guidelines for the application of these methods.

1.2 Overview of costing methods for advanced technologies

Three costing methods are summarized in this section: the engineering-economic method, the experience curve method, and the hybrid method that combines the first two. Further details on the use of each method are presented in subsequent sections of this report.

1.2.1 Engineering-economic method

This is the detailed bottom-up method commonly used to calculate the current cost of a project employing technology that is commercially available, often from multiple vendors. It is the principal method used by the Electric Power Research Institute (EPRI), , the U.S. Department of Energy's National Energy Technology Laboratory (NETL) and others for technology cost estimates. Details of the method as applied to power plants were described in an earlier white paper prepared by an international Working Group [15]. That same general framework applies equally well to other industrial processes, with adjustments for unique items and nomenclature in a given industry.

While that effort advanced the systematic use of relevant cost categories by major R&D organisations and firms, some differences are still found in cost-related nomenclature across different organisations. The current chapter often references the terms used by NETL, whose publically available technical reports and cost methodology guidelines are widely used and cited by others. Those guidelines for engineering-economic cost estimates are described most recently in the 2019 report, "Cost Estimation Methodology for NETL Assessments of Power Plant Performance" [16]. They are based in large part on the costing methodology first developed by AACE International (formerly known as the Association for the Advancement of Cost Engineering), which established five classifications for cost estimates based on the

level of project definition and detail, with increasing levels of accuracy for the resulting cost estimates [17]. This also the basis for guidelines subsequently adopted by EPRI [18, 19]. A serie of additional reports provides further guidance on specific aspects and assumptions used in NETL studies [20].

Based on specified plant and process designs, the required energy and mass flow are calculated and used to size all major equipment and plant components. The total capital requirement is then calculated as shown in Figure 1-1, which illustrates how various components of capital cost are aggregated to yield the total as-spent cost (TASC) for a particular system. While many recent studies are for fossil-fuelled power plants, the cost categories in Figure 1-1 are generic and can be applied to any technology of interest. The cost methodology also defines in detail the procedure used to combine the capital cost with financial parameters and annual O&M costs to obtain the overall cost of electricity (COE) generation for a power plant in a given year. More commonly, annual O&M costs are assumed to be constant for all years of operation when calculating the levelised cost of electricity (LCOE) over the life of the plant.
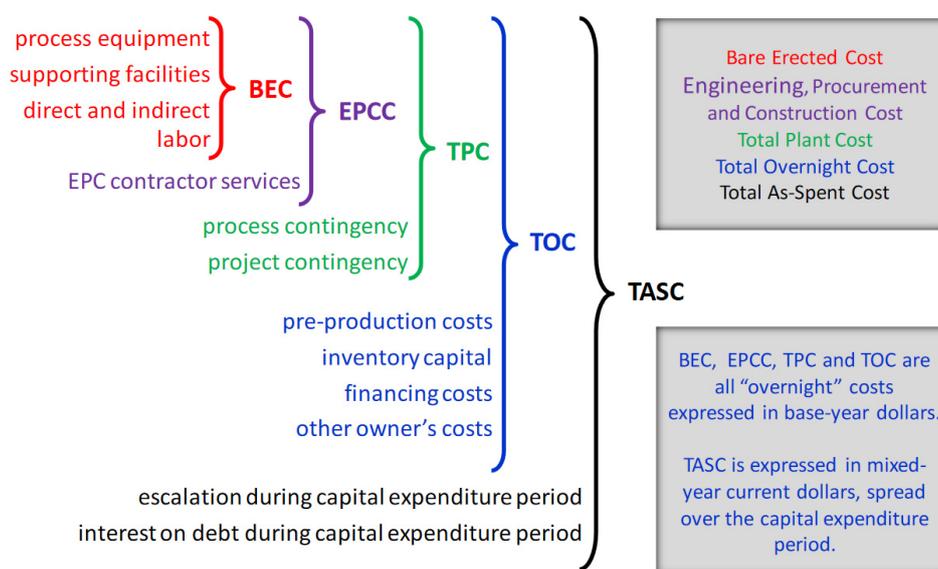
Figure 1-1. Schematic of the NETL engineering-economic method for capital cost estimates [16]

The basic building block of the engineering-economic cost estimate is an equipment list based on a specified process design and flowsheet that is intended to achieve a specified level of plant performance (e.g., output, efficiency, emissions, availability) over its lifetime. As indicated in Figure 1-1, the total cost of purchasing and installing all process or system components is generally referred to as the bare erected cost (BEC) [16]. Other capital cost elements in Figure 1-1 are typically estimated as a percentage of this amount (which some cost methods refer to as the total direct cost or process facilities cost).

For current commercial technologies, the BEC is commonly based on vendor quotes and/or recently published costs for major plant components. In some studies, such estimates are developed by a contractor providing engineering, procurement, and construction (EPC) services. Where such data are not readily available, equipment costs may be estimated using engineering handbooks, computer modelling software, or other methods [16, 21]. More complete descriptions of all cost items for power plant studies also can be found in Rubin, et al. [15]. **Readers of this chapter who are not already familiar with the AACE-EPRI-NETL cost study categories and methodology should review that earlier work, which is foundational to the current report, focused on advanced technology applications.**

1.2.1.1 Application to Type 1 (What If) questions

For advanced technologies that are not yet commercial and have not yet been built and operated at scale, a detailed engineering-economic cost analysis is appropriate to address Type 1 (What If) questions that are based on an *assumed* plant or process design with *assumed* values of technology performance and/or

cost parameters. By definition, such assumptions may or may not represent actual outcomes were the new technology to be built and widely deployed at scale. Typically, such analyses are carried out to assess the long-term potential and competitiveness of advanced technology components or novel plant designs and process integration schemes that meet specified performance and/or component cost goals. Such bottom-up studies, however, must take care to recognize that cost results represent a hypothetical case, and not a projection of the likely expected cost at some future time, given where the technology is today.

DOE/NETL regularly employs engineering-economic cost estimates for what-if studies of advanced technologies employing fossil fuels. Figure *1-2* illustrates typical results from one such study. In this case the technology is a power plant employing an integrated coal gasification fuel cell (IGFC) system to achieve higher efficiency than a conventional coal-fired power plant [22]. The results, based on computer modelling studies, show the incremental effects on overall plant efficiency and cost of meeting R&D goals for seven different parameters. This type of analysis asks what the overall plant cost would be *if* each technology component achieves specified goals for cost and performance. Typically, no specific timeframe is provided in this type of analysis.
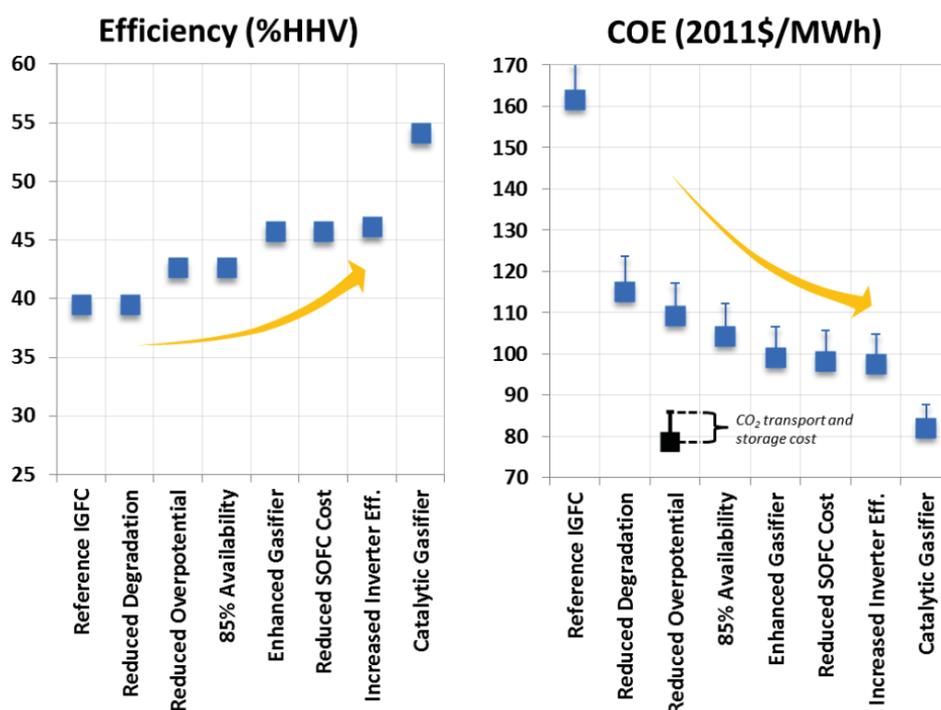
Figure 1-2. Cumulative impact on plant efficiency and cost of electricity (COE) of improvements in advanced IGFC technology [22]

Critical to analyses of this type is that the assumed values of certain performance and cost parameters be consistent with the premise of the analysis, e.g., an NOAK design for a mature technology. Section 1.3 of this chapter later elaborates on this topic.

1.2.1.2   Application to Type 2 (What Will) questions

As noted earlier, a detailed bottom-up cost analysis is not appropriate for an advanced technology if the objective is to estimate its actual cost at some future time when it has matured and been widely deployed. Rather, use of the engineering-economic cost estimate for what-will questions is appropriate only for a project to be built now or in the immediate future, based on current knowledge (and uncertainty) about the technology's performance and cost at scale. For an advanced technology that has not yet been built at scale, this near-term project would represent, by definition, the first-of-a-kind (FOAK) installation of a full-sized power plant or sub-system.

Section 1.4 later presents a more detailed discussion of how the engineering-economic method can be applied to estimate the FOAK cost of an advanced technology. Once such an estimate is obtained, it is then used in conjunction with the experience curve costing method to forecast the expected future cost of the advanced technology. The following section presents a brief review of the experience curve method.

1.2.2 Experience curve method

Experience shows that cost estimates for early-stage technologies tend to be optimistic and significantly lower than the actual cost of technologies that advance from research, development, and demonstration (RD&D) to commercial deployment at scale. Subsequently, the relatively high cost of early deployments tends to decline as the technology is adopted and matures, as depicted in Figure 1-3. This decline reflects a "learning rate" which can be estimated mathematically, thus providing an alternative costing method for advanced technologies once they reach the stage of large-scale deployment.
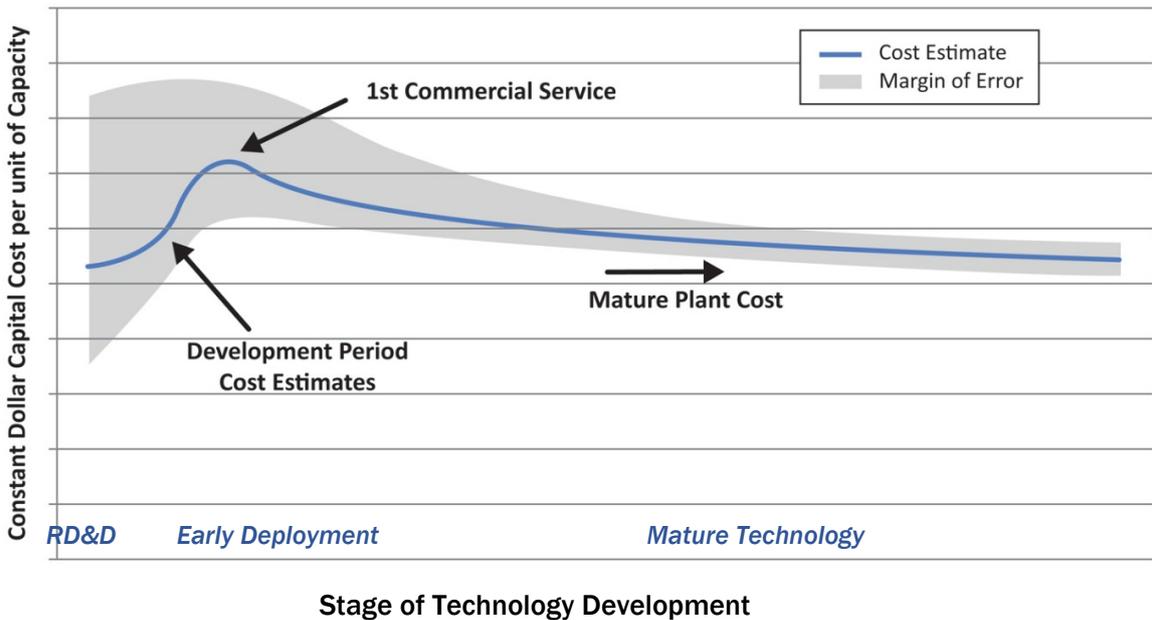
Figure 1-3. Typical cost trajectory of an advanced technology [23]

Figure footnote: the shaded area surrounding the curve reflects the varying level of accuracy associated with design estimates at different stages.

1.2.2.1 Empirical and theoretical framework

The use of experience curves—also commonly called "learning curves"—represents a top-down method of estimating the future cost of a technology based on historical trends for similar technologies. This method has its origin in the study of aircraft manufacturing in the 1930s, where it was found that the time required to construct a particular type of aircraft decreased in a predictable fashion as the task was repeated. Construction time versus cumulative production was found to be well-fit by a log-linear equation. Later, that equation was found to also fit observed trends in the capital cost of a variety of technologies as a function of cumulative production or installed capacity [24]. This experience curve equation is generally expressed as [25]:

$$y = ax^{-b} \qquad \text{(Eq. 1)}$$

where, for power plant capital cost:

y = capital cost per unit for the xth unit of plant capacity
a = capital cost per unit for the first (or initial) unit of capacity
x = ratio of cumulative to initial capacity of the technology
b = learning rate exponent

The empirical basis for such relationships typically reflects multiple generations of a technology deployed at plants of different sizes and designs. Cumulative installed capacity rather than number of installations is thus the most common independent variable used to develop experience curves. Some experience curve studies, however, use the cumulative value of energy production cost ($/MWh) as the independent variable, x, rather than cumulative capacity. Experience curve models based on Equation 1 also have been derived for annual O&M costs as well as for capital costs [26].

A defined parameter of learning curve models is the *progress ratio*, *PR*, defined as the fraction of the initial cost after a doubling of the initial capacity (i.e., a value of x equal to two). Thus:

$$PR = 2^{-b} \qquad\qquad\qquad (Eq. 2)$$

where, b is the exponent in Equation 1. A complementary parameter, widely used in the learning literature, is the **learning rate, *LR*, defined as the fractional reduction in cost for a doubling of the initial capacity.** Thus, the learning rate is defined mathematically as:

$$LR = 1 - 2^{-b} = 1 - PR \qquad\qquad\qquad (Eq. 3)$$

In this chapter, learning rate is used as the preferred measure of cost reductions achieved through technological learning, reported either as a decimal value or as a percentage. Given an observed value of the learning rate, the numerical value of the exponent b can then be calculated from Equation 1 and Equation 3 as:

$$b = -\log(1 - LR) / \log(2) \qquad\qquad\qquad (Eq. 4)$$

Figure *1-4* illustrates graphically the exponential decline in cost for different learning rates as a function of the cumulative deployment of a technology based on an arbitrary unit cost of 1000 for the first unit of capacity. In this example, learning rates range from 1 percent to 30 percent cost reduction for each doubling of cumulative capacity. As shown later in Section 1.2.2.2, this range encompasses most of the empirical values found for energy-related technologies.
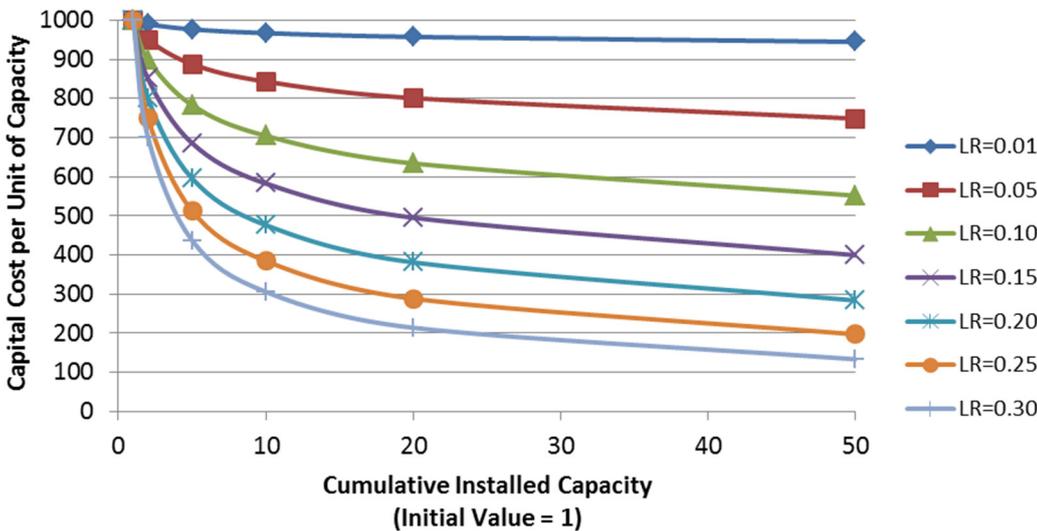
Figure 1-4. Illustrative cost trends for different learning rates

Equation 1 also can also be re-written as a linear equation by taking the logarithm of each term, yielding:

$$\log y = \log a - b (\log x) \qquad\qquad\qquad (Eq. 5)$$

This log-linear form is often used to display experience curve data. As illustrated in Figure *1-5*, the result is a linear decline in cost with increasing cumulative capacity on a log-log scale.
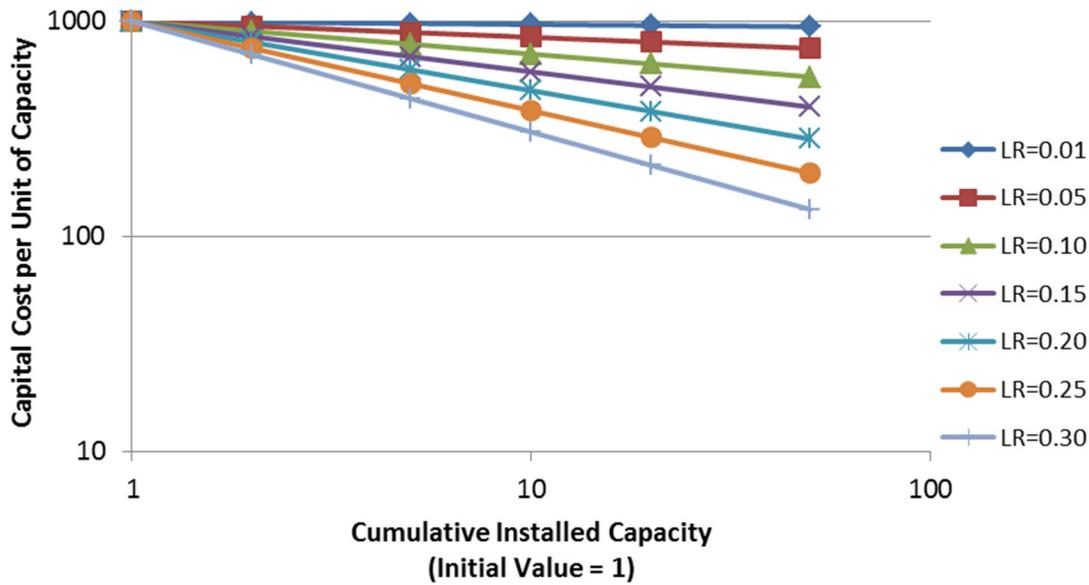
Figure 1-5. Illustrative cost trends for different learning rates on a log-log scale

Research on energy technologies also has sought more complex multi-factor model formulations to explain observed cost trends, especially the effect of R&D spending (also referred to as the "knowledge stock") on technology cost. Thus, there are examples in the literature of experience curves of the form:

$$log\ y = \alpha + b_{lbd}\ (log\ x) + b_{lbr}\ (log\ R) \tag{Eq. 6}$$

where, α is the specific cost at unit cumulative capacity and unit knowledge stock, b_{lbd} is the "learning-by-doing" parameter, b_{lbr} is the "learning-by-researching" parameter, R is the cumulative R&D investment, and y and x are as defined earlier in Equation 1.

While multi-factor models of this type that distinguish learning-by-doing from other factors that influence an experience curve are conceptually appealing, data to support them quantitatively are typically sparse. Thus, a recent literature review showed that the one-factor experience curve given by Equation 1 is the most prevalent model across a wide range of studies and energy technologies, with only a few multi-factor models, primarily for wind turbine power plants [27].

1.2.2.2 Learning rates for energy conversion technologies

Studies of learning rates for energy-related technologies have included a wide variety of electric power generation technologies and other large-scale energy conversion systems, as well as small-scale devices like energy-efficient air conditioners and light bulbs [28]. Among these, the most heavily-studied technologies have been renewable energy systems utilising wind and solar energy. Relatively few studies have been reported of past learning rates for industrial processes.

Table 1-1 summarizes the one-factor learning rates found from studies of power generation and other energy-related technologies. The data come from several recent papers, each of which reviewed and summarized peer-reviewed journal studies of learning rates for energy-related technologies. All rates shown are for new facilities and may not apply to retrofit installations with unique site-specific cost elements. In addition to learning rates based on observed cost reductions in the past, several of the review papers also reported expected future learning rates for selected technologies based on modelling studies or other estimates. Several of those "prospective" learning rates also are included in Table 1-1 and are designated by italics to distinguish them from historical rates. Another recent review paper [29] also reports learning rates from both retrospective and prospective studies, but does not present separate summaries of those categories. The reported learning rates again are predominantly from wind and solar PV systems, with values similar to those in Table 1-1.

One general observation from these data is that modular/standardized technologies that are produced in large quantities (such as solar PV modules) are typically more conducive to faster technological learning and cost reductions than more complex technologies that are tailored to specific circumstances and produced in smaller quantities (such as nuclear power plants).

Table 1-1. Learning rates for electric power generation and related technologies showing the percentage reduction in unit capital cost (or O&M cost) for each doubling of cumulative installed capacity or production, based on peer-reviewed literature sources.

Energy Source and Technology	N[a]	Learning Rate[b]				Source
		Range	Mean	Error[c]	Units	
Coal						
Pulverized coal plant (PC)	4	5.6% to 12%	8.3%		GW	[27]
FGD system	1		11%		GW	[26]
FGD system (O&M cost)	1		22%		GWh	[26]
SCR system	1		12%		GW	[26]
SCR system (O&M cost)	1		13%		GWh	[26]
Coal[b]	*1*	*−5% to 5%*	*0%*		*GW*	[30]
PC+CCS[b]	*2*	*1.1% to 9.9%*			*GW*	[27]
IGCC[b]	*2*	*2.5% to 16%*			*GW*	[27]
IGCC+CCS[b]	*2*	*2.5% to 20%*			*GW*	[27]
Natural Gas						
NGCC	5	−11% to 34%	14%		GW	[27]
Gas Turbine	11	10% to 22%	15%		GW	[27]
NGCC+CCS[b]	*1*	*2% to 7%*			*GW*	[27]
NGCC[b]	*1*	*2% to 15%*	*6%*		*GW*	[30]
Nuclear						
Nuclear plants	4	negative to 6%	-		GW	[27]
Nuclear plants	3	−49% to 22%	−44%		GW	[30]
Nuclear (business as usual)[b]	*1*	*−25% to 0%*	*−15%*		*GW*	[30]
Nuclear (optimal conditions)	*1*	*0% to 10%*	*5%*		*GW*	[30]
Biomass						
Power generation[d]	2	0% to 24%	11%		GW	[27]
Power generation	1		6%		GW	[30]
Hydroelectric						
Hydroelectric plant					GW	[27]
Fuel Cells						
FCEV fuel cell stacks			18.0%	1.7%	GWh	[31]
PEFC micro-CHP			19.3%	1.6%	No. units	[31]
Fuel cells (residential)		16% ± 2%[e]			GWh_{cap}	[32]
Hydrogen						
H_2 (alkaline electrolysis)			17.7%	5.3%	GW	[31]
H_2 (SMR)			27%		10^9 cu.ft.	[26]
H_2 (SMR) (O&M costs)			27%		10^9cu.ft.	[26]

Table 1-1. (cont'd)						
Wind						
Onshore	12	−11% to 32%	12%		GW	[27]
Onshore (1982-2016)			5.9%	1.3%	GW	[31]
Onshore (2009-2016)			24.5%	2.1%	GW	[31]
Offshore	2	5% to 19%	12%		GW	[27]
Offshore			10.3%	3.3%	GW	[31]
Onshore[b]		*−3% to 12%*	*5%*		GW	[31]
Offshore[b]		*−5% to 10%*	*3%*		GW	[31]
Solar						
PV system					GW	[27]
PV systems			18.6%	1.0%	GW	[31]
PV modules			21.4%	0.8%	GW	[31]
PV balance of system (BOS)			12.9%	1.7%	GW	[31]
CSP plants[b]	5	*3% to 12%*	*10.4%*		*GW*	[30]
PV (short-term)[b]	1	*15% to 23%*	*20%*		*GW*	[30]
PV (long-term)[b]	1	*8% to 17%*	*12%*		*GW*	[30]
CSP plants[b]	1	*3% to 12%*	*8%*		*GW*	[30]
Energy Storage						
Utility Li-ion storage			15.2%	3.7%	GWh$_{cap}$	[31]
Utility redox-flow storage			14.3%	6.1%	GWh$_{cap}$	[31]
Residential Li-ion storage			12.5%	3.0%	GWh$_{cap}$	[31]
BEV battery packs			15.2%	2.9%	GWh$_{cap}$	[31]
HEV battery packs			10.8%	0.6%	GWh$_{cap}$	[31]
Pumped hydro (utility)		−2% ± 8%[e]			GWh$_{cap}$	[32]
Other Technologies						
Heat pumps			10.0%		No. units	[31]
LNG production			14%		Mt/yr	[26]
LNG prod. (O&M costs)			12%		Mt/yr	[26]
Oxygen production			10%		10^9 cu.ft.	[26]
Oxygen prod. (O&M costs)			5%		10^9 cu.ft.	[26]
Energy Efficiency						
Specific energy use (GJ/t)		12% to 29%			Mt product	[33]

[a] Number of studies. Some studies report multiple values based on different datasets, regions, or assumptions
[b] LR values in italics reflect model estimates or other projections, not historical data; all values are reported as percentages rather than decimals; negative learning rates indicate increasing (rather than decreasing) costs; "Units" refers to x-axis quantity.
[c] Standard error equals square-root of the diagonal of the variance-covariance matrix.
[d] Includes combined heat and power systems and biodigesters.
[e] 95% standard error confidence interval

Note too that learning rates, properly derived, relate cost reductions with increasing experience in doing the same "job"—such as installing a unit of power plant capacity, generating a unit of electricity, or capturing a fixed percentage of air pollutant emissions (e.g., 90 percent SO_2 capture using an FGD system). If the nature of the job changes—such as capturing only 50 percent SO_2 instead of 90 percent— the historical learning rates in Table 1-1 may no longer apply. Similarly, negative learning rates typically reflect changing technology design requirements.

Table 1-2. Additional learning rate estimates based on expert judgment for selected technologies [23]

Cost Category/Technology Type	Learning Rate	Cost Category/Technology Type	Learning Rate
Category 1		*Category 6*	
Coal Delivery and Handling	1% – 4%	Advanced Combustion Turbines	4%
Category 2		Syngas Combustion Turbines	5%
Coal Prep and Feed	1% – 4%	Hydrogen Combustion Turbines	5%
Category 3		Natural Gas Combustion Turbines	1%
Feed Water/Misc. BOP	1% – 5%	*Category 7*	
Category 4		Heat Recovery Systems	1%
Boiler Equipment & Aux.	1% – 9%	*Category 8*	
Gasifier Systems	4% – 21%	Steam Turbines	1%
Syngas Cooling	4% – 21%	Advanced Steam Turbines	4%
Air Separation Units	3% – 15%	*Category 9*	
Category 5		Cooling Towers/Systems	1%
Syngas Clean-up	3% – 15%	*Category 10*	
Acid Gas Removal	3% – 17%	Ash/Slag/Spent Sorbent Handling	2%
Particulate Removal	3% – 17%	*Category 11*	
Mercury Removal	3% – 17%	Power Distribution System	1%
Warm Gas Clean-up	3% – 17%	*Category 12*	
Sulphur Recovery	3% – 17%	Instruments & Controls	1%
Flue Gas Clean-up	2% – 17%	*Category 13*	
Particulate Removal	2% – 17%	Site Preparation	1%
SO_2 Removal	2% – 17%	*Category 14*	
NO_x Removal	2% – 17%	Buildings & Structures	1%
Mercury Removal	3% – 17%		
Syngas Conversion	3% – 5%		
Fischer-Tropsch Synthesis	5%		
Methanol & Ethanol Production	3%		
CO_2 Capture, Recovery	3% – 18%		
CO_2 Compression	5% – 10%		
Fuel Cells	2% – 6%		
Direct Liquefaction Process	6%		
CH_4 From Hydrates	6%		

Table 1-2 shows additional estimates of learning rates for technologies and plant components that lack modelled or historically-based learning rate studies. Accordingly, these rates are based primarily on the expert judgment of power-sector cost estimators, with upper bounds informed by selected literature on energy technology learning rates [23]. Such estimates may be useful in the absence of retrospective or prospective learning rates for a technology of interest. The learning rates derived from historical experience curves are commonly employed to address Type 2 (What Will) questions about the expected future cost of an advanced technology once it is widely deployed commercially. Section 1.5 discusses the selection and application of learning rates to carry out such projections, including estimates of expected N^{th}-of-a-kind costs.

1.2.3 Hybrid method

The hybrid costing method introduced in recent work [3] refers to a combination of the engineering-economic and experience curve methods of cost estimation discussed above. It was developed to address Type 2 questions for advanced technologies. The section describes the method and its use.

1.2.3.1 Combining bottom-up and experience curve analyses

The use of an experience curve to project the future cost of a technology requires as its starting point the current cost of a commercial-scale system. In the hybrid method, a bottom-up engineering-economic analysis is thus used to first estimate the current capital and operating costs of a full-scale commercial project. For an advanced technology that has not yet been built at scale, this would represent the FOAK cost for a plant employing that system.

From this starting point, an experience curve is then used to project future cost reductions as the technology is further deployed. The need for experience in building and operating full-scale plants is inherent in the experience curve model since cost reductions are a function of the cumulative installed capacity or production. Cumulative capacity also reflects the time it takes to learn from experience with multiple generations of a technology as it evolves. After a sufficient amount of deployment with decreasing levels of change, the technology can be considered to be mature, corresponding to the concept of an NOAK plant.

1.2.3.2 Illustrative example for Type 2 questions

Figure *1-6* illustrates the use of the hybrid method and the type of results derived from this approach. This is an ideal case where the first commercial installation successfully achieves all performance requirements. As the cost of the advanced technology then declines from its current (FOAK) value (at installed plant capacity, C1), the analysis reveals the cumulative installed capacity, C2, needed to match the current lower cost of a competing baseline technology that is currently available commercially. Continuing down the curve shows the additional level of experience, C3, needed to achieve a still lower cost target or goal. Similar curves for other advanced technologies can allow one to identify the technologies that are likely to meet cost goals most quickly.
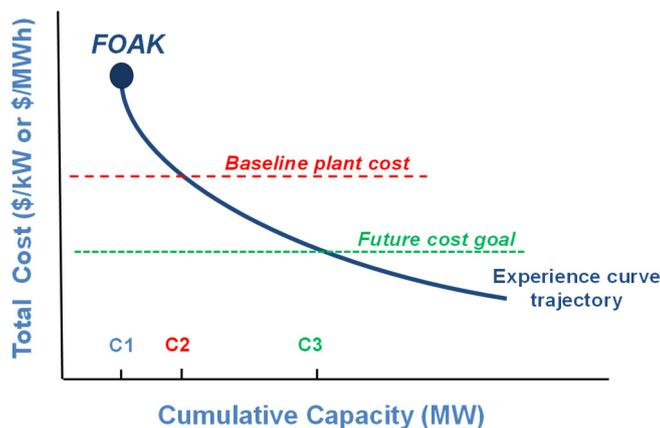
Figure 1-6. Illustrative cost trajectory of an advanced technology from FOAK plant to mature plant showing the deployment of the technology needed to meet a given cost goal.

Note that this formulation does not have an explicit value of NOAK cost since there is no unique value of N (or cumulative capacity) at which a technology is considered to be mature. As a rule of thumb, however, the cost trajectories in Figure *1-4* show that cost tends to level out and decline slowly once cumulative experience reaches about 15 to 20 replications (4 to 5 doublings) of the initial capacity. At that point, a technology can reasonably be labelled as mature, as it is well-established and likely being offered by multiple vendors competing for future sales. For a mid-value learning rate of 0.15 the cost after four

doublings has fallen to roughly half its initial value. Note too that the area under the curve between any two points represents the total plant investment needed to go from one point to the other.

1.2.4 Strengths and limitations of alternative methods

The three costing methods described above have different strengths and weaknesses depending upon the uses to which they are put and the questions they are employed to address. In the context of cost estimates for advanced power plants and other energy conversion technologies, as well as low-carbon industrial processes, the strengths and weaknesses of each method are highlighted below.

1.2.4.1 Engineering-economic method

In general, the strength of the engineering-economic method is that it can provide a rigorous and accurate cost estimate for a well-defined process or plant design if employed with appropriate data and parameter assumptions. Thus, as noted earlier, it is appropriate to address what-if questions about the overall cost of a plant whose design, performance, and component costs are fully specified. For advanced technologies, such specifications typically represent a hypothetical mature (NOAK) plant design that meets specified performance and component cost targets.

Conceptually, this method is best suited to estimate the current cost of a commercial project that would be built now or in the very near future—i.e., what-will questions about the current cost of a technology or its next commercial offering. It is primarily intended (and most widely used) for costing a facility employing technologies that are already in commercial use. For an advanced technology that has not yet been built and operated at scale, the output of this method would be the FOAK cost. That cost estimate would have to rely on what is currently known about the technology's performance and other attributes such as the cost of novel components. A higher degree of technical and professional judgment is also required since reliable information is typically lacking for early-stage technologies (such as the cost of fabricating a unique piece of equipment that has never been built at scale). The FOAK cost estimate for a new technology is thus inherently more uncertain than one for a more mature technology, resulting in more conservative assumptions and higher contingency costs (as elaborated later in this paper). The methodological approach of the bottom-up method is nonetheless appropriate for this application.

The principal weakness of the engineering-economic method in the context of this chapter is that is not suited or appropriate for addressing what-will questions about the future mature-plant cost of an advanced technology that is still under development. As noted earlier, that is because one cannot know today what the future design, performance, and component costs will be of a new technology that is many years (typically decades) away from the concept of an NOAK facility. Rather, future NOAK plant designs and technology component costs evolve with experience and cannot be established reliably without first deploying and operating multiple commercial plants over a period of time. Thus, a bottom-up analysis of a proposed future design is essentially a "what-if" exercise that simply *assumes* that the future NOAK design, performance, and cost assumptions are viable and will be achieved. Effectively, it is an estimate based on the judgments and opinions of the analysts or other experts who conduct the analysis.

Another significant shortcoming of a bottom-up analysis for a future NOAK plant is that it does not provide a timeframe in which the future performance and cost are expected to be achieved. At best, a time dimension might be estimated based on the judgment of the analyst or others involved in the cost estimate. While experience curves also do not provide an explicit measure of time, the cumulative installed capacity is a surrogate that can be linked directly to elapsed time via a deployment scenario or past experience with the rate of technology deployment.

1.2.4.2 Experience curve method

The principal strength of the experience curve method is that it is grounded in actual historical experience on the rates and magnitudes of cost reductions for technologies that are successfully adopted and deployed in the marketplace. Further, by linking cost reductions to cumulative deployment of a particular technology, it implicitly brings time into the picture as a key variable characterising cost trends. The

relationship between cumulative capacity and time also can be made explicit via energy-economic modelling (e.g., van der Broek, et al., 2009) in which advanced technologies are deployed in the context of a particular scenario, such as a "business as usual" reference case or a proposed policy scenario. Thus, experience curves provide a dynamic model of cost reductions that evolve over time as technologies are deployed and continually improved. A schematic of that process of technological change is shown in Figure *1-7*.
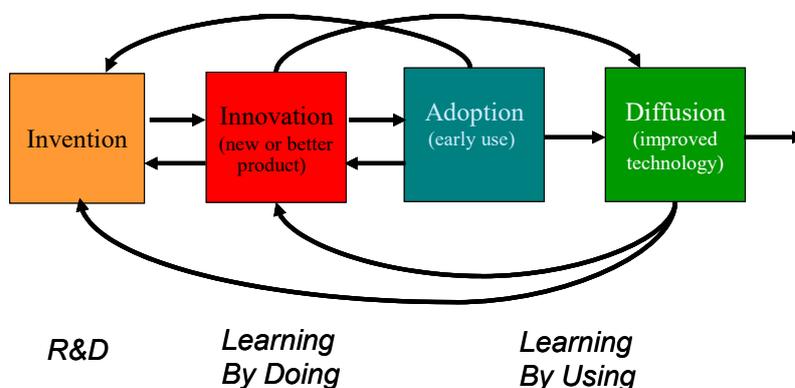
Figure 1-7. The dynamic process of technological change and innovation [34]

An acknowledged shortcoming of cost projections based on historical experience curves is that the single parameter on which most models are based (e.g., cumulative installed plant capacity) is effectively a surrogate that incorporates all other factors that influence cost reductions in addition to true "learning by doing" (which represents efficiencies in manufacturing and construction). Other factors include such things as the level of R&D investments, scale economies, market conditions, and level of competition among firms [35]. Also, because of data limitations and availability, most experience curves are based on the price paid for a technology (i.e., the cost to the customer) rather than the cost of production or manufacture (which is the true measure that underlies learning by doing).

In addition, the experience upon which the learning rates are based may not necessarily apply to a different technology in the future. As seen in Section 1.2.2.2 above, there is also a wide variation in learning rates across the set of technologies that have been studied. Thus, the selection of a learning rate for a particular advanced technology cost projection is not straightforward. Guidance on such selections, however, is offered in Section 1.5 of this report, including how to deal with cases where an advanced technology involves a mix of novel and mature components. Uncertainties in experience curve rates and models, including their shape, are discussed in Section 1.6.

Another limitation is that cost projections based on learning rates offer no specific insights as to precisely why costs decline or how technology designs evolve and change over time. Thus, one can only estimate what a mature (NOAK) plant is expected to cost, not what it is likely to look like. However, past studies of energy and environmental technologies indicate that economies of scale, competition among firms, lower-cost manufacturing, knowledge sharing, and sustained R&D are among the key factors that contribute to long-term cost reductions [14, 36].

Finally, any use of experience curves to estimate the future cost of an advanced technology requires an independent estimate of the current commercial cost of the technology and its level of deployment, from which cost reductions are assumed to begin. This need is addressed using the hybrid method discussed earlier.

1.2.4.3 Hybrid method

The strength of the hybrid approach to cost estimates for advanced technologies is that it combines the strengths of the engineering-economic and experience curve methods to address what-will questions about future costs. Thus, a bottom-up engineering-economic analysis is first used to estimate the current cost of a commercially-deployed plant based on current information about the advanced technology design, performance, and cost. Section 1.4 of this chapter provides guidelines on the construction of that FOAK cost estimate. Next, an experience curve model is used to provide an empirically-grounded projection of the future cost trajectory, beginning with the current cost. This approach thus avoids the use of assumptions about the future technology design and the future cost of components or systems that have not yet been built and operated at scale. This approach also explicitly recognizes the critical role of experience with full-size plant construction and operation in achieving future cost reductions. Thus, the hybrid approach offers a critical parameter that is lacking in traditional bottom-up cost estimates, namely, a measure of the time (embodied by cumulative experience) needed to achieve significant cost reductions. The hybrid method can be applied to complex plant designs involving multiple components with different levels of maturity and different learning rates, as illustrated in Section 1.5.

As with its component methods, the hybrid method can be subject to significant uncertainties, both in the estimation of current (FOAK) plant costs as well as in the future cost trajectory for advanced technology components. The same would be true, however, of any other method of estimating the future cost of a technology. Section 1.6 discusses uncertainty characterisation in greater detail.

Finally, a limitation of the hybrid method is that it does not explicitly incorporate the potential for capital or other cost *increases* during early deployment, as seen in a number of historical case studies [26]. To the extent such increases occur (e.g., due to shortfalls in initial reliability or performance, or a lack of competitive markets), the proposed hybrid method may yield systematically optimistic cost projections by underestimating the true FOAK cost (as would other costing methods). Methods and guidance for dealing with this issue are discussed in Section 1.5.

1.3 Guidelines for future cost estimates for Type 1 (What if) questions

This section focuses on several key assumptions and inputs to a bottom-up cost analysis of a hypothetical new plant employing an advanced technology that is considered to be mature and widely deployed. Given that the methodological details of a bottom-up costing method are already well-documented (e.g., [6, 16, 19]), **the guidelines in this chapter emphasize the need for assumptions that are consistent with the premise of the "NOAK cost goal" analysis.** The following sections briefly highlight several areas where past studies were often deficient or inconsistent in the reporting of key assumptions.

1.3.1 Plant and process design assumptions

The starting point for any bottom-up cost analysis is the specification of plant and process flowsheets that establish the major pieces of equipment together with mass and energy flows for the given design. The study in Figure *1-2*, for example, assumed an advanced coal gasification system with warm-gas clean-up coupled with a solid oxide fuel cell system, an ion transport membrane-based oxygen plant, and an advanced hydrogen-fired gas turbine. The overall plant was modelled in a commercial software system (Aspen Plus) to determine the mass and energy flows used to size all equipment for specified component performance characteristics.

For a "what if" analysis of a hypothetical mature plant using one or more advanced technologies, **the principal guidance for plant design is to explicitly state all assumptions regarding the major plant equipment, battery limits, redundant equipment, and the size (and size limits) of major plant components**. Equipment size limits might be expressed in terms of a maximum flow rate (mass or volumetric), or maximum equivalent generating capacity (MW), of a single vessel or item, given constraints on construction or commercial offerings. Depending on the size of the overall facility being

analysed, multiple vessels or equipment trains may therefore be needed for some components. This has a direct impact on capital costs.

Some plant components also may be oversized to accommodate off-design conditions, and some equipment may require a degree of redundancy (sparing) to ensure reliability. Here too, such assumptions have a direct impact on plant cost. Studies must therefore state assumptions about equipment overdesign and redundancy or indicate clearly if all equipment is assumed to exactly meet maximum design flow rates with no redundancy.

Similarly, **the principal guidance for plant and process performance is to explicitly state** key **design and operating assumptions for the assumed NOAK plant**. This includes principal mass and energy flows; pollutant removal efficiencies and associated energy and reagent requirements of all major plant equipment; and specification of all plant products and product quality, where applicable. Other useful information includes descriptions and basis for system or process flowsheets, physical property models, and any other unique attributes of an advanced technology.

1.3.2   Capital and O&M cost assumptions

Given the hypothetical nature of an NOAK cost estimate, authors have fairly wide latitude in the assumptions for underlying capital and operating cost parameters. Again, the key need is for consistency with the stated premise of the analysis, and transparency in the source or basis for component cost assumptions.

1.3.2.1   Bare erected cost

As indicated in Figure 1-1, the major building block for capital cost estimates is the bare erected cost (BEC) of the stipulated plant design. As noted earlier, for an NOAK plant, that cost is typically based either on specified (pre-established) cost targets for advanced technology components, or on cost estimates from other sources. Section 1.4.2 later provides additional guidance on the quantification of plant equipment costs. For the hypothetical plants in Figure *1-2*, the BEC was based almost entirely on R&D cost targets specified by DOE/NETL, as well as on "vendor-furnished projections for next generation technology" [10, 23].

However, **most studies fail to sufficiently explain how the assumed BEC cost targets or projected values were determined**, leaving it up to the reader to judge whether the resulting BEC is reasonable, achievable, or consistent with the methods employed in other studies of other technologies. Thus, the reported value of BEC for an advanced technology - which is the building block for total cost estimates - is arguably the most poorly documented and least transparent component of an estimated hypothetical NOAK cost.

Thus, **NOAK cost studies should always discuss the methods and data sources used to obtain BEC estimates. To avoid ambiguity about the cost basis, good practice also demands that the cost year be clearly (and repeatedly) reported, as well as the location to which the BEC estimate applies.**

In this regard, the IEAGHG recently published a set of location-specific cost factors that give the relative costs of materials and labour in twelve geographic regions worldwide (see Table B-1 in Appendix B) [37]. Cost variations within a region also should be considered using other sources of country-specific data (for example, for U.S. power plants the IECM computer modelling tool adjusts the BEC for six geographic regions based on U.S. data for materials and labour costs) [38]. In addition, information on the current cost of advanced technology components should be provided to give context to the BEC estimates, and help readers assess the degree of progress required to achieve the assumed NOAK cost values.

Finally, to add a degree of conservatism and credibility to hypothetical NOAK cost estimates, **we recommend that estimates of the future Bare Erected Cost of a mature technology take into consideration the actual current state of that technology.** This is because the future BEC of a technology currently at a low TRL value is inherently more uncertain and speculative than that of a

technology at a higher TRL. NOAK studies should therefore report whether (or how) such considerations are reflected in the BEC estimate. One approach would be to incorporate the cost adders recommended by NETL and EPRI as "process contingencies" (which vary by process maturity) directly into the BEC estimate for the hypothetical NOAK design. This would help temper the "technological optimism" that often characterizes BEC cost estimates for technologies that are still at an early stage of development. As discussed below, a subsequent process contingency factor would be applied based on the "what if" assumption of a mature technology.[3]

1.3.2.2 Process contingency cost

In bottom-up cost estimates, the process contingency cost is the capital cost added to the BEC to compensate for uncertainties associated with the development status of a technology based on its current level of maturity or development. The quantitative guidelines adopted by EPRI, NETL [18, 19] and others were developed many years ago by AACE International [16, 17] (see, [6]). Effectively, this is an estimate of the additional (miscellaneous) capital costs that are expected to be incurred in a near-term commercial project based on the current state of information and experience for the technology under study. Thus, the initial (FOAK) deployment of an advanced technology would incur a much higher process contingency cost than an established commercial technology, as elaborated later in Section 1.4.2.2.

However, in the case of a "what-if" NOAK cost estimate in which an advanced technology is assumed to be fully mature, **the process contingency cost should be consistent with the premise of the analysis—in this case, that of a mature commercial system.** The NETL and EPRI guidelines cited earlier provide a numerical range of 0–10% for such estimates (see Table 1-5). While such values may seem unrealistically low given the actual development status of an advanced technology, it is nonetheless consistent with the premise of a mature technology whose future design and cost are assumed to be known today.

Note too that the project contingency factors in Table 1-5 do not depend on the degree of engineering detail underlying the analysis, as they do for project contingency factors (discussed below). Other recent studies of project cost estimates, however, suggest that higher process contingencies also should apply to less detailed preliminary analyses compared to more detailed studies for investment decisions (e.g., see Table B-2 in Appendix B) [40]. This methodological limitation of most current cost analyses tends to result in underestimates of true cost for the classes of study most commonly employed for advanced technology assessments.

To add a degree of conservatism to advanced technology cost estimates, some Type 1 NOAK studies assume the higher process contingency cost factor applicable to the current (less mature) status of the technology. However, that remains inconsistent with the definition of this factor and the premise of a mature technology for "What If" studies. Instead, as noted in Section 1.3.2.1, we recommend that this higher cost factor be incorporated (transparently) into the Bare Erected Cost of the advanced technology. Then, based on the assumption of a mature technology, a lower process contingency factor would be applied to the BEC, as prescribed by the engineering-economic methodology. This approach would also provide a measure of methodological consistency across studies of different advanced technologies.

Methodological consistency and transparency are especially important for technology cost comparisons, which are often the objective of NOAK cost studies. Often, however, studies fail to report their assumptions regarding contingency costs, resulting in a lack of transparency that leaves doubt as to whether contingency costs were even included in the analysis, and whether the reported costs are therefore biased downward. **Clear and full reporting of contingency cost assumptions (as well as BEC**

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[3] The concept of Commercial Readiness Level (CRL) also has been developed to reflect the additional uncertainty and risk remaining in the deployment phase of commercialization due to factors such as the capabilities and capacity depth in supply chains, engineering services and other factors that may affect the cost of FOAK and subsequent projects. This has been applied mainly to renewable energy technologies where access to capital has also been a barrier to accelerated deployment [39].

assumptions) thus remains critical. It is then up to the audience for such cost estimates (including reviewers and editors of technical journals) to judge their credibility.

1.3.2.3 Project contingency cost

The project contingency cost is an additional capital cost item that accounts for the cost increases that typically occur with increasingly detailed information on site-specific costs. The cost factor guidelines originally established by AACE International and subsequently adopted by EPRI and NETL, call for higher values in studies with less site-specific detail [16, 19, 41]. However, reviews of recent studies found that assumed project contingency cost factors are systematically low relative to established guidelines—especially for "budget-type" cost estimates that are common for advanced technology studies [8, 9]. The result is to understate the estimated capital cost by as much as 10%–30%. Thus, **NOAK cost estimates should be careful to include the project contingency cost factors that are consistent with the level of site-specific detail of the study.**

1.3.2.4 Other capital cost factors

Figure 1-1 lists the additional elements of a capital cost estimate, which include pre-production costs, inventory capital, financing costs, capital cost escalations and interest on debt during construction, and other "owner's costs" that are enumerated in guideline documents for engineering-economic cost estimates (e.g., [4, 6, 16, 19]). Readers should consult those documents for more detailed guidance on how to quantify these factors for commercial technologies. Again, **for Type 1 questions the values chosen should be consistent with the premise of a mature NOAK technology.**

1.3.2.5 Operating and maintenance costs

O&M costs can be a significant component of overall cost, especially for advanced technologies that require large amounts of energy for their operation, or which use new materials not currently manufactured in large quantities. Examples include advanced CO_2 capture processes employing large temperature or pressure swings, or which employ advanced materials such as ionic liquids, metal-organic frameworks, solid sorbents, or new types of membrane materials.

The prevailing assumption for O&M costs in NOAK studies is that advanced technologies achieve specified performance and cost targets (e.g., for new materials). Seldom, however, do studies report the current cost of such materials or technologies, or discuss the means whereby the future cost goals are expected to be achieved. Thus, it is again left to the reader to judge whether assumptions about future cost are reasonable in the context of a particular study. As good practice, **the rationale for assumptions about O&M costs should be discussed and justified** in order to assist readers in judging the credibility of an NOAK cost estimate. For a complete list of O&M cost factors and guidance on quantification readers should again consult the reference cited above in Section 1.3.2.4.

1.3.3 Financing and plant utilisation assumptions

For either power plants or other industrial processes, the total capital requirement of the project is amortized over the expected life of the plant and then combined with annual O&M costs to calculate an overall cost per unit of product, either on a year-by-year basis or, more commonly, on a levelised annual basis. For power plants the common metric is the levelised cost of electricity (LCOE). For other industrial processes it is the levelised cost of product (LCOP). For plants that produce multiple products a principal product must be identified. Two key parameters for this calculation are highlighted below.

1.3.3.1 Weighted average cost of capital

The weighted average cost of capital reflects the overall cost of money borrowed or invested to finance a project using various sources of debt and equity financing. Together with the project lifetime, this rate determines the capital charge rate (also called fixed charge factor, FCF) that is used to amortize the total capital cost. Note that these rates can be expressed either in *nominal* (current money) terms that include an assumed rate of inflation, or in *real* (constant money) terms that exclude inflation effects. While the

latter is most common and recommended for technology comparison studies (e.g., [6]), some studies employ nominal rates. Thus, **it is critical that studies clearly report the cost basis used.**

In general, the weighted cost of capital reflects the degree of risk associated "with a project—riskier projects involving new or early-stage technologies typically demand higher financing rates than mature, established technologies that have been widely replicated. By definition, however, **NOAK projects are assumed to be mature, low-risk technologies that enjoy a low-risk cost of capital.** In some past studies, however, the assumed cost of capital for an advanced NOAK technology was based on a high-risk project, which is inconsistent with the NOAK premise of a mature system. The result is to overstate the cost of the assumed NOAK plant. **Cost of capital assumptions should be consistent with the assumed premise of the study.**

1.3.3.2 Plant capacity factor

The annual average capacity factor (CF) of a power plant reflects the fraction of electricity actually generated in a year relative to the maximum possible generation if operated for a year at the full rated capacity. The value assumed for CF is arguably the most important parameter affecting the unit cost of electricity ($/MWh) since it determines the amount of electricity over which the capital investment is spread. Thus, the higher the CF, the lower the cost per unit of electricity generated. Depending on how a power plant is operated (e.g., load-following vs. on-and-off at full capacity), lower capacity factors could also increase the plant heat rate (efficiency), and thus its LCOE.

For purposes of this report, **guidance for NOAK studies again emphasizes the importance of CF assumptions that are consistent with the study premise, including assumptions about how the NOAK plant is operated.** This guidance also emphasizes that for LCOE calculations, **the assumed CF should be the levelised value over the life of the plant.** This weighs initial years of operation more heavily than later years because of discounting (see, e.g., [8]).

Historical data on the capacity factor of mature coal-fired and gas-fired power plants over their operating life offer one credible benchmark for numerical assumptions about the future CF of a new NOAK plant. Although time series data on the CF individual generating units over their full operating life are not readily available, one case study of a large coal-fired unit reported a 25-year average capacity factor of 77% from 1981-2005, with a levelised CF of 71% due to the characteristically lower CF during the first years of operation [8].

The U.S. Energy Information Administration (EIA) also publishes aggregated capacity factor data for U.S. power plants on a monthly and annual basis. Such data show, for example, that for coal-fired units the average plant capacity factor from 2010 to 2019 fell from 67% to 48%, while for natural gas combined cycle (NGCC) units the average capacity factor rose from 44% to 57% [42]. Thus, over the past two decades, the utilization of both coal and natural gas plants has been well below their annual average availability of approximately 85% [43]. This applies also to large newer coal units, whose mean CF in any year was approximately five percentage points higher than the overall coal plant average based on data from 1998 to 2009 [8].

Other parts of the world show similar CF trends that are well below the typically assumed availability values of 85–90% [44, 45]. Looking ahead, power plants with and without CCS are expected to continue to have gradually reducing capacity factors as the grid share of intermittent renewable energy sources increases in the future (e.g., [46]).

Assumptions about the operating hours of a hypothetical NOAK plant therefore require careful consideration and justification, especially if the assumptions depart significantly from historical trends. Many recent cost studies, for instance, assume that power plant capacity factor is equal to the plant availability, meaning that the unit is dispatched at its nameplate capacity any time it is available (e.g., [12]). One rationale for this assumption is that the study objective is "to compare technologies based on their performance and cost merits without imposing market forces that would impact CF" [43]. Thus,

in view of the historical data noted above, **an assumption that the levelised capacity factor over the life of a plant is equal to its availability is a bounding case that yields the theoretical minimum value of LCOE for the technology analysed.** Based on historical data, the actual expected CF would be lower and the estimated LCOE higher. **This distinction between expected and bounding values of CF and LCOE should be clearly acknowledged in NOAK cost study results that employ that assumption.** Failure to highlight this distinction can easily lead to misunderstandings that would bias comparative cost results and technology rankings based on LCOE.

1.4   Guidelines for FOAK Cost for Type 2 (What will) questions

As outlined earlier in Section 1.2.4.3, the starting point for the hybrid approach to addressing "What Will" questions about the future cost of advanced technologies is an estimate of the current cost of a commercial plant employing the technology. For an advanced technology that has not yet been built at a commercial scale, this would be the FOAK plant cost. In other cases, it would be the "next-of-a-kind" commercial project. In either case, the methodological approach is a bottom-up engineering-economic cost estimate similar to the one described in Section 1.3 for a mature plant, except that now all cost parameter values are based on a first-of-a-kind (or next-of-a-kind) plant design.

This section of the chapter highlights a number of areas where FOAK design and cost factors often differ significantly from NOAK estimates. The guidelines presented here draw heavily on a recent report on FOAK cost estimation prepared for NETL by Black & Veatch, an engineering, procurement, consulting and construction company with broad experience in the electric power sector [47]. The FOAK guidelines also draw on the existing guidelines for conventional power plant cost estimation [16, 19], as well as on recent experience with FOAK projects employing power plant CO_2 capture or other large-scale energy technologies [40, 48, 49]. Wherever possible, quantitative guidelines are provided in addition to qualitative discussions related to FOAK cost estimates.

In general, **FOAK cost estimates are most appropriate for technologies that have advanced to at least a large pilot plant or full-scale testing of the new process or system** (e.g., TRL 6 or 7) to provide the basis for further scale-up and integration for a full-scale commercial facility [47]. Though FOAK cost estimates also may be carried out for technologies at earlier stages of development, such technologies are inherently much riskier. **Because of their higher risk, FOAK cost estimates must therefore also reflect the greater difficulty such projects would face in obtaining the financial and technical resources needed to actually undertake a commercial-scale project.**

As a starting point, a number of initial screening questions can help frame cost estimates for advanced (pre-commercial) technologies [47]. For example: How long has the technology been in development? What is its current level of maturity? How have the risks associated with design, construction and operation of the technology been fully characterized and incorporated into the design and cost elements? Appendix A provides a more comprehensive list of screening questions and their relevance to FOAK cost estimates.

1.4.1   Plant and process design factors

As with cost estimates for mature plants, estimates for FOAK plants begin with a specification of the plant and process designs and the battery limits of the project. For FOAK or other early-stage projects, the design is likely to include a greater degree of spare or redundant equipment, oversized vessels and other items that would not be found in mature plants, but which are incorporated in early designs to help ensure reliable operation and desired performance. While such measures do not guarantee that the FOAK plant will indeed operate reliably as designed, the risk of failures or shortfalls are minimized by a more conservative design in the absence of prior (or limited) experience.

1.4.1.1   Equipment Sizing, Overdesign, and Redundancy

Development of the FOAK design basis typically involves three phases [47]. The first is equipment sizing based on design flows, pressures, and other sizing-related measures. Next, an overdesign (or margin) is applied to ensure flexibility, safety, and resiliency in system operation. Typically, these design margins also account for operation at various ambient temperatures, and for and differences in feedstock properties (especially for coal-based plants). Lastly, redundancy is provided as additional protection for critical equipment in order to avoid forced outages and unnecessary downtime.

The most common applications of design margins are for essential equipment which must operate constantly, such as pumps, fans, and valves. Certain pieces of critical equipment, including large rotating machineries such as power plant steam turbines and flue gas fans, have an additional need for redundancy in some of their components. For example, to avoid potentially catastrophic equipment failure if oil flow to the bearings of a large steam turbine is interrupted, the lubricating and hydraulic oil skid for the turbine often utilizes 2x100% or 3x100% redundancy for motors, filters, and bypass valves. Similarly, large centrifugal or axial fans are typically designed for 2x100% redundancy for critical motors, valves, and bypass lines [47].[4] In these cases, redundancy is applied to mature technologies as well as to FOAK installations.

However, for advanced technologies being built at scale for the first time, or with little prior operating experience, the need for spare (redundant) equipment to reduce risks is typically far greater than for mature technologies. Thus, early-stage technologies commonly employ redundancy not only for critical items like pumps, values, and fans, but also for major vessels that are critical to the operation of the new technology. For example, early deployments of wet flue gas desulfurization (FGD) systems at large coal-fired power plants in the 1970s frequently employed a spare absorber train in addition to several operating trains because of reliability concerns. Similarly, many proposed designs for early-stage integrated coal gasification combined cycle (IGCC) power plants employed a spare gasifier along with several operating units. Only as process designs and scale improve with cumulative deployments and operating experience does the need for equipment redundancy decline or disappear.

The need for redundancy of FOAK technology or sub-systems with little or no operating experience at the scale envisioned should be determined based on a review of the factors that might cause a shutdown or poor performance of the technology. Such considerations would include the degree of scale-up, the duration and results of previous testing under a range of operating conditions, and the depth of technical understanding of the factors that affect the performance and reliability of the technology.

Inevitably, decisions about redundancy in FOAK designs reflect a balancing of risks (e.g., the consequences of a malfunction or failure of the technology to operate as expected) versus the added cost of spare equipment that will not be utilized if all goes as planned. A careful vetting of the proposed design can help identify critical needs for additional process development to avoid unnecessary redundancy that inflates the project cost estimate [47].

For illustrative purposes, the following are examples of typical redundancies for commercial-scale plant equipment [47]:

- **1x100%.** No redundancy; typical for large plant components that are mature and proven in prior experience, as well as for small blowers, non-critical valves, and tanks.
- **2x50%.** No redundancy, since a single unit cannot carry the full rated load; however, partial service is maintained if one unit fails. This is most commonly used for pumps or blowers that cycle on and off periodically and are not critical to plant operation.
- **3x50%.** Partial (50%) redundancy; however, a risk that no single unit can fully support the process if two of the units should fail simultaneously.

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[4] A designation of Nx100% means N pieces of equipment each capable of handling 100% of the flow. Thus, 2x100% means one operating unit plus one spare unit that can be put into service if the operating unit fails.

- **2x100%.** High degree of redundancy and a common configuration for critical pumps, fans, and/or safety valves (with an option for both components to be run at half capacity for faster response to transient conditions).
- **3x100%.** Potentially excessive redundancy, but could be warranted for a pump or compressor train that is critical for the safety of personnel and plant equipment.

For advanced technologies that have not yet reached commercial scale, FOAK designs for a full-scale plant may require the use of multiple vessels or trains due to limits on the size of available FOAK or early-stage equipment. For example, in the case of FGD systems noted above, early commercial equipment was often limited to flue gas flow rates equivalent to roughly 150 MW of power plant capacity. A 450 MW plant therefore required at least three operating absorbers for SO_2 capture. Due to reliability concerns, a spare train was often added to early designs (i.e., 33% redundancy). Similar levels of redundancy may be appropriate for advanced technologies with analogous characteristics.

In other cases, a novel technology at commercial scale may require dozens or hundreds of modules, reactors, or vessels operating in parallel. In such cases, a significantly lower level of redundancy would be expected based on the known or anticipated failure rate of individual modules. For example, a process that required 200 vessels operating in parallel at full load might be designed with only five spare vessels (2.5% redundancy) to provide enough redundancy to operate through unplanned equipment outages or malfunctions, while also promoting cost-effectiveness Black & Veatch [47].

In summary, as illustrated in the examples above, there are no hard-and-fast rules for the precise level of redundancy in FOAK designs. Rather, each project requires an evaluation based on the criticality of process components and sub-systems, the extent of prior testing and experience, and the cost of critical technologies. In all cases, however, **an explicit redundancy philosophy should be provided in all cost studies to ensure that this issue has been carefully considered and addressed appropriately.**

1.4.1.2   Other Factors Affecting FOAK Plant Design

The following items are recommended best practices for contract management and process design for a pre-commercial or FOAK technology cost estimate. All of these factors apply as well to a Type 1 (aspirational NOAK) cost estimate, though the time and cost implications are different for FOAK and NOAK projects. The discussions of each item were provided by Black & Veatch [47]:

- **Target standard materials in process design.** While hybrid or specialized materials can be attractive due to their unique or superior properties, material pricing, supplier availability and long-term maintenance considerations may indicate that other standard materials provide a more robust design option.

- **Understand applicable codes and standards.** Early alignment of the FOAK design with the National Electric Code (NEC), National Fire Protection Association (NFPA), International Building Code (IBC), and other applicable codes will avoid potentially costly design iterations and expedite third-party assessments and due diligence reviews.

- **Incorporate realistic operability measures**. These include controls, feedback measures, and safety protections so that when forced outages and equipment malfunctions occur the system has built-in methods to safely recover and operate until the situation is mitigated.

- **Identify critical legal and contractual mechanisms needed to mitigate performance and schedule risks**. A firm strategy for how these contractual items will be accounted for during project execution for FOAK technology is important for financing and insurance underwriting entities. Common items between equipment suppliers and end-users needed to secure a final contractual agreement include: performance and/or schedule liquidated damages; performance guarantees; limitations of liability; and, warranty periods.

- **Perform a hazard and operability analysis of the plant and/or process.** This provides evidence that design risks have been mitigated and that safety has been designed into the plant. In particular, the concept of "safety by design" has gained rapid adoption in the industry [47].

- **Inclusion of start-up, shut-down systems.** This is an important requirement that is often overlooked in FOAK designs.

Another critical factor for a pre-commercial technology is the level of risk associated with the project design and construction schedule. Table 1-3 outlines critical FOAK technology project risk areas that should be considered when developing the design and execution plan for a facility incorporating pre-commercial technology [47]. In general, a higher level of risk results in higher project costs. The following sections of the chapter discuss more fully the cost items that are influenced by the design factors and risks identified in section 1.4.1. To help quantify the impact on plant cost of these (and other) systemwide risks, a new cost factor is introduced below in Section 1.4.2.3.

Table 1-3. Risk evaluation metrics for pre-commercial technology project planning [47]

Risk Factor	Low Risk	Medium Risk	High Risk
Project Schedule	Sizeable project float[a] between engineering, procurement, and construction phases	Aggressive schedule with complex scope but adequate float	Minimal to no float between project phases; all activities are critical path
Technology Maturity (Performance Risk)	More than 10 successful installations with more than 1 year of operation per site	3-10 successful installations with 0.5-1.0 years of operation per site	Less than 3 successful installations with less than 0.5 years of operation per site
Number of Sub-Suppliers and/or Sub-Contractors	1-5 equipment suppliers within the project	5-10 equipment suppliers with moderate-high experience	More than 10 separate suppliers with low to moderate experience

[a] "Float" refers to the time gap (margin) between the planned end date and the (earlier) critical path end date for a project activity.

1.4.2 Capital cost factors

Once the FOAK design is specified, the next step is to estimate its current capital cost based on the present state of technology development. Conceptually, this involves the same general procedure outlined earlier in Figure 1-1 for a bottom-up analysis, i.e., first estimate the bare erected cost of the plant, then apply other indirect cost factors and contingency costs to calculate the total capital requirement [16].

1.4.2.1 Bare Erected Cost

In general, the BEC for a first-of-a-kind project will be significantly greater than for a mature technology or a plant assumed to meet R&D goals. Key contributors are more conservative designs (including oversized and redundant equipment), longer construction schedules, and the use of new components or materials that are not yet widely fabricated or produced in large quantities or sizes.

The most robust method of developing a BEC estimate for a commercial project is to employ an independent third-party entity with experience in estimating construction and sub-contractor costs for large-scale construction projects. For a pre-commercial technology, this type of arrangement often can be protected by a non-disclosure agreement (NDA) which, in the U.S., would typically take 3-6 months at a cost of roughly $100,000 to $200,000, depending on the level of complexity and detail involved [47]. Most published cost estimates fail to include such costs, however.

If this option is not available or feasible (e.g., for a preliminary study), a BEC estimate for an advanced technology also can be developed based on guidance from cost estimation software (e.g., AspenTech [50])

as well as from a variety of widely-used textbooks and references on process equipment design and cost estimation (e.g., [51-53]). Where available, recent cost studies based on vendor quotes for other processes or equipment with similarities to the advanced technology under study also can be useful for bounding and scaling a BEC cost estimate. While the cost derived from any of these methods are subject to uncertainty (see Section 1.6), **a careful effort to ensure that first-of-a-kind considerations are fully reflected in the BEC cost estimate is critical to this step-in cost estimation.**

It is also helpful to compare the FOAK BEC estimates to those of current commercial technologies to help ensure that such estimates are reasonable and that all applicable plant design and equipment sub-categories have been addressed. For power plant studies, for example, Figure 1-8 depicts the percentage breakdown of BEC components reported by Black & Veatch [47] for commercial PC and NGCC plants without CCS recently analysed by NETL [43]. For advanced pre-commercial technologies, the BEC values in the relevant process area accounts would be expected to exceed the commercial system values for plants of similar overall design.
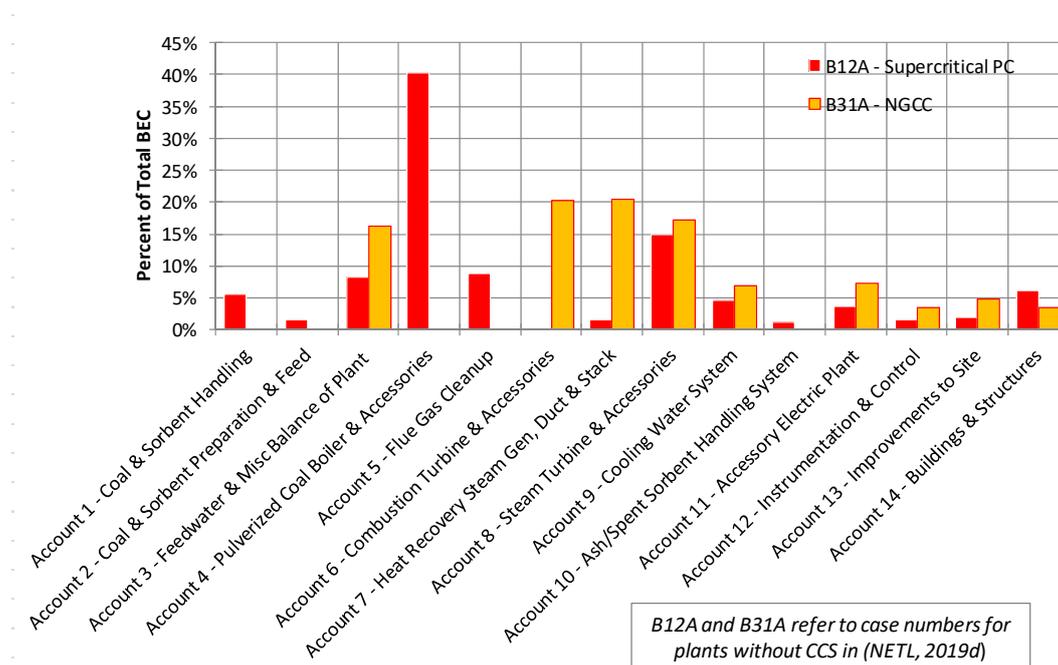
Figure 1-8. BEC breakdown by process area for commercial PC and NGCC plants [47]

1.4.2.2 Process and project contingency costs

As noted earlier in Section 1.3.2.2, capital cost estimates commonly include two types of contingency costs: process contingency and project contingency. The latter depends solely on the level of site-specific detail in the cost estimate (whatever the technology). Thus, **guidance for project contingency cost estimates is the same for both FOAK and NOAK plants.** See Section 1.3.2.3 for details or, e.g., AACE International [41].

In contrast, **the process contingency cost differs significantly for FOAK and NOAK cost estimates** since it depends on the experience base and maturity of the technology in question. As indicated in current cost guidelines [16, 19], the method of quantifying process contingency cost is to apply a percentage of the total installed cost of the process or technology in question. Table 1-4 shows the recommended values for processes at different levels of maturity. These guidelines, first developed by AACE International [17], also have been adopted by EPRI [18, 19]. Approximate TRL values corresponding to the AACE descriptions of technology status also are shown in Table 1-4.

39

Table 1-4. Process contingency cost guidelines [16, 19]

Current Technology Status	Indicative Equivalent TRL Value	Process Contingency Cost (% of associated process capital)
New concept with limited data	~3	40+
Concept with bench-scale data	~4	30-70
Small pilot plant data	5-6	20-35
Full-sized modules have been operated	7-8	5-20
Process is used commercially	9	0-10

Because advanced (pre-commercial) technologies vary widely in their complexity and degree of novelty, the contingency cost factors for each of the five development level categories in Table *1-4* also have a wide range. Professional and technical judgments are thus required to select an appropriate value based on the current status of technology development and an assessment of the risks in scaling up to a commercial FOAK facility. An uncertainty analysis for capital costs would ideally encompass the minimum and maximum values judged to be appropriate for a particular study.

The key guidance conveyed by Table 1-4, however, is that in contrast to assumptions for NOAK cost studies, which commonly assume process contingency factors of zero to 10 percent (as for a mature commercial process), **appropriate values of process contingency costs for pre-commercial FOAK studies are several times higher than for NOAK cost studies.** The particular value selected may be more or less conservative, depending upon the judgment of the cost estimator and the purpose of the study.

Additional guidance provided by Black and Veatch [47] is that the process contingency factor for any individual component should seek to be less than 40 percent, as higher values would indicate that the process is not suitably defined or understood for a full-scale project. This perspective implies that the process status in Table 1-4 should be at least at the "small pilot plant data" level (e.g., TRL 5-6) to avoid excessive risks in FOAK cost estimates for a commercial-scale project. For processes currently at earlier stages of development, FOAK cost estimates based on more limited data nonetheless require much higher process contingencies, as indicated in Table 1-4.

Another independent perspective on contingency cost guidance is provided in a 2014 study that reviewed the actual and estimated costs for ten recent large-scale energy projects in Australia [40]. As a result, that study also recommended substantially higher process and project contingencies to bring initial cost estimates in line with actual final costs. The total contingencies recommended for projects at different stages of development and cost studies at different levels of granularity are generally higher than current NETL guidelines. That study further recommended an additional indirect cost item called "supplemental funds" to provide a financial buffer for project investors to deal with less likely "extraordinary situations" that may occur during the definition and/or implementation phase of a project (for example, a change in the project site, significant plant design changes, a need to re-route a CO_2 pipeline, and/or changes in access to critical infrastructure such as high voltage transmission or plant water supply). These guidelines also were recently published in a peer-reviewed journal article and employed for an advanced technology cost estimate (Larsen, et al., 2020). Table B-2, in Appendix B, summarizes these guidelines as an additional reference for FOAK and NOAK cost estimates, and Figure B-1 (in Appendix B) shows some of the underlying data for these guidelines.

Because contingency cost values for FOAK projects often have broad ranges, the resulting cost estimates also have a higher degree of uncertainty than projects employing mature technologies. Section 1.6.1 discusses uncertainty and risk analysis methods to characterize those uncertainties, including probabilistic methods of evaluating contingency and overall project costs.

1.4.2.3 System Contingency Cost

Advanced technologies often combine new or established process components in novel ways that have not yet been implemented at a commercial scale. One example is the IGFC power plant design in Figure *1-2*, which integrates advanced gasifiers, oxygen plants, fuel cells, gas turbines, and other components into a unique system. Another example is a calcium looping CO_2 capture system, which combines several commercial components in a new way [54].

In all such cases, increased system complexity and novel integration schemes introduce new risks that tend to reduce the overall reliability of FOAK installations. As a result, additional costs are likely to be required to achieve and maintain the design level of performance. Even where only a single new process is integrated into a conventional plant for the first time, interactions with other system components can cause unexpected problems and process outages that require additional expenses to rectify (e.g., [55]). These additional system-level costs can be significant but are not typically reflected in the process contingency cost factors described earlier, which depend only on the maturity of individual plant components (see Table 1-4).

To account for additional capital costs related to system integration and complexity, an additional contingency cost factor is introduced here, called *system contingency* cost. This factor is uniquely applicable to the initial installations of a new technology or system design, where integration-related problems first arise. It is similar in nature (though smaller in magnitude) to the "supplemental funds" factors discussed above and shown in Appendix B. It is also similar in nature (and magnitude) to the location-specific cost factor recently introduced by IEAGHG [37] to account for "additional potential execution risks" associated with the implementation of a large CCS project. Those factors are shown in the last column of Table B-1 in Appendix B.

Pending further data acquisition and analysis efforts to quantify this factor, the guidance in Table 1-5 is suggested by the authors of this chapter to ensure that this potential cost adder is not overlooked in FOAK cost estimates. The suggested value of this factor, informed by the studies of Greig, et al. [40] and IEAGHG [37], is greatest for the first commercial installation. The system contingency cost then decreases for subsequent projects, assuming that any systems-related problems found at a FOAK installation will result in design changes (and associated cost increases) to eliminate the problem in subsequent replications. To the extent that initial design changes are not wholly successful, some risk for subsequent early-mover projects may remain, pending demonstration that the reliability problem has indeed been resolved successfully. Thereafter (nominally after five replications of a project), the system contingency goes to zero. However, for any non-zero values of the initial (FOAK) system contingency cost the bare erected cost likely will have increased as a result of design changes in each of the early projects.

Table 1-5.   Proposed system contingency cost guidelines

Technology Status	System Contingency Cost (% of total process capital for all newly integrated components)
First commercial-scale project (FOAK)	0 – 20
Second and third commercial projects	0 – 10
Fourth and fifth commercial projects	0 – 5
All subsequent commercial projects	0

A key distinction from the process contingency cost is that the system contingency cost factors depend only on the level of prior experience with the integrated system and not on the maturity of the individual technological components. Thus, mature technology components integrated in a unique fashion for the

first time would have the same system contingency factor as advanced technology components that are combined for the first time. Since the system contingency cost factor has not been incorporated in prior engineering-economic cost estimates, ranges are suggested with a lower bound of zero in all cases (representing no additional risk from system integration). Analysts are encouraged to use their professional judgment in selecting a value appropriate for the context and degree of conservatism sought in the FOAK cost estimate.

1.4.2.4   Other FOAK Cost Factors

Two additional capital cost factors for pre-commercial technologies are highlighted based on contractor experience [47]: cost escalations during construction, and the cost and scheduling impacts of required permits.

Escalation of capital costs during project planning and construction is a standard factor in cost estimation (see Figure 1-1), but FOAK projects are susceptible to greater escalation since project EPC schedules are typically longer than for NOAK projects. Thus, incorporation of a real cost escalation rate is recommended for any project with more than a six-month duration to provide additional confidence in the overall cost estimate [47]. Numerical assumptions would depend strongly on economic conditions in the region and industry of the study, and should be informed by current information on price trends for relevant materials and equipment.

C**ost and schedule requirements for obtaining necessary permits** to operate a FOAK facility are often overlooked in the initial stages of advanced technology development. While permitting costs also are a standard element of bottom-up cost estimates [16], pre-commercial technologies typically require longer schedules and higher costs than mature technologies. This would also apply to certain new classes of permits, such as a Class 6 underground injection well for storage of CO_2 from a CCS system, Thus, a prudent step in cost estimation is to prepare a table of all necessary permits required for plant operation, as illustrated by the "permitting matrix" in Table 1-6 (with hypothetical entries for several common permit types). Often, a third-party specialist or consultant is engaged to prepare this information once a project location is specified [47].

Table 1-6.   Illustrative example of a project permitting matrix (actual entries may vary) [47]

Regulation	Regulatory Agency	Permit Submittal Format	Permitting Timeframe	Risks
Building Permit	'Smith County' Planning Dept.	Submittal and approval of construction plans	10-20 days	Low Risk – Common application and current projects indicate standard processing time
Clean Water Act Section 404	U.S. Army Corps of Engineers	Individual or nationwide permit	6-12 months	Low Risk – Common application; can be mitigated by avoiding existing wetland areas
'Smith County' Planning/Zoning Approval	'Smith County' Planning Development	Conditional use permit	Estimated at 6-12 months	High Risk – No project work can begin without approved Conditional Use Permit
Other Local, State or Federal requirement	Agency Name	Permit submittal format	Estimated time for approval	Estimated risks to project schedule

1.4.3   O&M cost factors

Details of O&M cost categories and estimation methods are illustrated in a recent NETL cost study [43] and other references (e.g., [6]). In general, estimated O&M costs for FOAK technologies or projects are expected to be higher than for an equivalent NOAK installation. The sections below discuss some of the considerations in estimating the magnitude of FOAK costs. **In all cases, reporting and justification of**

assumptions for the fixed and variable O&M cost parameter highlighted below are imperative for a credible cost estimate.

1.4.3.1 Variable O&M cost items

Analogous to an LCOE calculation for a power plant, this calculation would combine the estimated capital costs (for buildings and equipment), O&M costs (for feedstock materials, labour, utilities, etc.), and financing cost to estimate a cost (or price) per unit of product at the production scale needed for the FOAK facility. Such an estimate, if feasible, would provide a reasonable bound for purposes of a FOAK cost estimate.

All other VOM costs can be estimated following the standard cost guidelines cited earlier. Note that the NETL methodology [16] considers the maintenance costs for planned and unplanned equipment outages to also be variable cost items. Here too, prudence would suggest that these estimated costs also will be higher for FOAK installations where reliability data are lacking.

1.4.3.2 Fixed O&M Cost Items

Fixed O&M (FOM) costs are typically higher for FOAK facilities because of the likely needs for increased maintenance labour, operating labour, and engineering to support the operation of a new technology. Estimates of these requirements should be developed and incorporated into the FOAK cost estimate. Labour productivity assumptions also are critical, as many project cost overruns have been attributed to worse than predicted productivity. All other FOM costs can be estimated following the NETL guidelines cited earlier. Several of these cost items also are likely to be higher for FOAK facilities than NOAK projects (see Table 1-7). In these cases, adjustments to NETL guideline values for current commercial technologies should be made based on the nature, complexity, and current maturity of the advanced technology being incorporated into the FOAK facility.

Table 1-7. Examples of increased fixed O&M costs expected for FOAK projects (Based on [47])

Fixed Cost Item	Reason for Higher FOAK Cost Relative to NOAK
Regulatory Fees	A FOAK facility operating new technology is expected to have higher regulatory cost exposure than an NOAK facility.
Professional Services (accounting, legal, etc.)	Legal support in the form of supplier warranty management, claims management, and overall commercial risk mitigation is expected to be greater for a FOAK facility and the primary contributor to higher cost.
Tools/Equipment	In general, new and/or novel (FOAK) technology is expected to require more special tools and plant maintenance equipment.
Lease Expenses	In most cases, a FOAK facility is expected to operate for a shorter period of time than an NOAK facility and thus pay higher land lease rates (since shorter lease occupancy periods typically incur higher lease payments).
Training	For a unique FOAK technology, there is low likelihood of knowledge transfer of maintenance technicians, plant operators, and plant engineers from other similar facilities; therefore, significant initial and ongoing training is likely to be required for FOAK facility staff.
Property Taxes and Insurance	Due to a lack of prior commercial experience, a FOAK facility will likely incur higher insurance premiums for industry-aligned coverage.

1.4.4 Financing and plant utilization factors

As discussed earlier in Section 1.3.3, financing and plant utilization factors are used together with capital and O&M costs to calculate the levelised cost of electricity (LCOE) for a power plant. However, the numerical values of financial and plant operating variables assumed for FOAK plants will differ from those for mature NOAK plants. In general, FOAK values for these parameters reflect the higher level of

risk associated with first-of-a-kind projects. This, in turn, increases the LCOE relative to NOAK assumptions.

The key financial factors that distinguish FOAK projects from NOAK facilities are the weighted cost of capital and the expected lifetime (book life) of the project. These are the principal determinants of the fixed charge rate (FCR) used to amortize the capital cost of a project (see NETL [16] for details). **Because FOAK projects lack prior operating experience, they typically incur a risk premium in the form of a higher cost of capital for project financing.** Past NETL studies, for example, assumed a "high risk" weighted cost of capital that was 10% (0.7 percentage points) higher than the "low risk" (also called "commercial") cost of capital [10]. Others, however, assume much larger differences (e.g., several percentage points) between high-risk and low-risk projects. In general, however, the magnitude of the risk premium and cost of capital for a FOAK facility will depend on the circumstances of the particular project and the risk profile of the pre-commercial technology. Technologies that are still in the earlier stages of development would be expected to have higher risk premiums for a commercial-scale installation than those that are closer to commercial deployment.

Some FOAK projects also are planned to have a shorter operating life than a conventional new facility (e.g., an advanced technology retrofitted on an existing power plant with a 20-year remaining life). For a given cost of capital, a shorter project lifetime produces a higher capital charge rate, resulting in a further increase in the estimated LCOE. Therefore, the assumed project lifetime should be carefully considered and reported in any FOAK cost study.

Finally, **the levelised capacity factor over the life of the FOAK plant also is likely to differ significantly from the value assumed for an NOAK facility.** Two general factors contribute to this difference. One is the perspective or purpose of the cost analysis (i.e., what if vs. what will). The other is the technical readiness and reliability of the advanced technology being costed.

A bottom-up **FOAK analysis to address a Type 2 (What Will) question should employ the most realistic capacity factor** for the pre-commercial technology under study. This is in contrast to the bottom-up NOAK analysis discussed in Section 1.3, which was motivated by a Type 1 (What If) question for a hypothetical facility meeting specified criteria and assumptions that may or may not be achievable—including assumptions about CF.

Section 1.3.3.2 earlier presented illustrative data on the recent historical values of capacity factor for U.S. fossil fuel power plants. Such data can serve as a benchmark and guide for FOAK facilities resembling current plants. Historical data also are available from the EIA for other plant types. In some cases, estimates of future load factors may be available from detailed capacity planning models for a particular region. For new plants, it should be kept in mind that the first few years of operation typically have lower utilization levels during the break-in period, which has a significant impact on the levelised value due to the effect of discounting [8]. This is especially important for FOAK facilities because of their characteristically slower ramp-up rates as bugs are ironed out over the initial years of operation. In all cases, **the choice of levelised capacity factor also should be based on a consideration of how the facility under study is expected to operate** (e.g., baseload vs. cycling or peaking), along with the frequency and duration of planned outages.

Capacity factor assumptions also should take into consideration the likelihood that an advanced technology being built and operated at a commercial scale for the first time will have several years of higher forced outage rates than a commercial technology [47]. This is likely to further reduce plant capacity factors during the initial years of operation, which weigh most heavily in levelised value

calculations.[5] Thus, **the levelised capacity factor for FOAK cost estimates should be less than that of a similar commercial facility.**

1.4.5 Towards a future NOAK plant

The capital and O&M cost estimates for a FOAK installation discussed above provide the starting points for estimates of the actual expected cost of a future mature plant if the advanced technology is successfully commercialized and adopted broadly. Additional assumptions about the future financial and plant utilization factors of an NOAK facility contribute to a projection of expected LCOE. Section 1.5 below elaborates on the guidance for such cost projections.

1.5 Guidelines for NOAK cost for Type 2 (What Will) questions

This section of the chapter elaborates on guidelines for conducting the type of hybrid cost analysis discussed in Section 1.2.3 and depicted graphically in Figure 1-8. Beginning with the current (FOAK) cost of an advanced technology, empirically-based learning rates are applied to estimate its future cost assuming it is successfully commercialized and widely adopted.

Methodologically, these guidelines adopt the basic procedures outlined in a 2014 NETL report [23], which drew heavily on work published by the International Energy Agency Greenhouse Gas R&D Programme [26, 56]. Those guidelines noted that many advanced technologies of interest are single process components that are integrated into an otherwise mature system, such as a commercial power plant. For more complex advanced technologies, a new methodological feature is the additional system contingency cost (Table 1-5) that is ascribed to the overall plant rather than a particular sub-section.

The overall cost of the system (e.g., the LCOE) is also an important metric of interest, with additional parameters whose values may change with experience. Accordingly, **there are five basic steps in estimating future component and plant costs using experience curves**:

- Step 1: Decompose the overall plant into major technology sub-sections.
- Step 2: Estimate the current overall plant cost and sub-section contributions.
- Step 3: Select appropriate learning rates for each major sub-section.
- Step 4: Set the starting point for learning and end point for future cost estimates.
- Step 5: Compute future sub-section and system contingency costs as a function of cumulative experience and aggregate for plant-level results.

    Each of these steps is discussed in the sections below.

1.5.1 Decomposing a plant into sub-sections

While the principal focus of this chapter is the future cost of an advanced technology (such as a novel CO_2 capture process), the most important cost metric for decision-making is often the cost of the overall plant or facility employing that technology. Frequently, the remaining components of such plants are commercial and widely-used systems, such as a conventional PC or NGCC power plant. Thus, the first step in a plant-level analysis using experience curves is to decompose the overall facility into sub-sections whose costs are likely to change at different rates for a given increment of new plant capacity.

For the case depicted above, where a new process or component is added to an otherwise mature plant design, two sub-sections may suffice: the advanced technology and the balance of the plant. In other cases, additional decomposition may be desired or helpful to refine the analysis. **The principal criterion for the choice of sub-sections is their level of technological maturity and operating experience**, as reflected by their cumulative installed capacity (the primary variable for experience curves, as discussed

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[5] In some cases, a plant may be able to continue operating without the advanced technology, such as a post-combustion CCS system that can be bypassed. In such cases, however, an adjustment must be made for the additional emissions that would occur while the capture plant is offline.

in Section 1.2.2.1). This is because a big percentage increase in the total capacity of a new technology (with a significant reduction in cost) typically corresponds to a relatively small change in the cumulative capacity of a mature technology that is already widely deployed. The result is a correspondingly small (often negligible) change in the cost of mature components, no matter what their learning rates (see Table 1-4).

In cases where there are significant differences in the current maturity of technological components, another consideration in the choice of plant sub-sections is the availability of appropriate learning rate data for the different technologies. Where such data are available (see Section 1.2.2.2), additional sub-sections may be warranted to refine the analysis. Table C-1, in Appendix C, illustrates the choice of plant sub-sections for four types of fossil fuel power plants equipped with new technologies for CO_2 capture.

1.5.2 Estimating current sub-section costs

Section 1.4 provided guidelines on estimating the current cost of a full-scale commercial facility that may include both advanced and mature technology components. For purposes of future cost projections for power plants **two cost measures are needed: the total capital requirement per unit of net plant capacity (typically $/kW) and the total annual O&M cost of the facility per unit of electricity generated (typically $/MWh)**. For other industrial processes, these costs would be normalized on the capacity and unit cost of the major product. FOAK values of financing and plant utilization factors serve as reference points for cost projections but are not typically subject to continuous experience curves; rather, new values of these parameters are assigned periodically as a technology matures, as discussed in Section 1.5.6 below.

As a starting point for future cost projections, **the total FOAK capital cost of the plant should be decomposed to obtain the cost of each sub-section** identified in Section 1.5.1. This exercise is usually straightforward since the plant-level capital cost is built up from the estimated costs of all plant components, as illustrated earlier in Table 1-4.

Similarly, **fixed and variable O&M costs also should be allocated to plant sub-sections**. This too is a straightforward procedure employing the component-level data used for FOAK cost estimates (see Section 1.4.3). Note that the cost of energy in the form of electricity and/or steam used to operate sub-section equipment is not considered to be a variable O&M cost item at the sub-section level if that energy is generated within the plant and not purchased from an external supplier (as is typically the case for integrated plant designs).[6] Rather, the requirements for electricity and steam are reflected in the net plant efficiency and the resulting plant-level requirement for purchased fuels such as natural gas or coal. Thus, **the total fuel energy requirement per unit of net plant output is tracked to account for all in-plant energy use.** A learning rate for this parameter then reflects any improvement in the overall plant efficiency as advanced technologies or other plant components mature.

1.5.3 Selecting sub-section learning rates

The choice of a learning rate for each plant sub-section is based on a judgment as to what technology or historical learning rate (or range of rates) offers the best match or proxy for the plant area in question. It also depends on the purpose or objective of the analysis and the questions or decisions it is intended to inform.

Section 1.2.2.2 summarized the learning rates reported in recent studies and literature reviews for power plant and related chemical process technologies. In general, the experience curve literature is focused mainly on capital costs; relatively few studies report learning rates for annual O&M costs. Overall,

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[6] For purposes of estimating the total cost of an individual plant component, some cost studies do include a cost for energy drawn from within the plant, treating it as if it were a purchased commodity. However, such cost assumptions are arbitrary since there is no unique way to ascribe a unit price (e.g., $/MWh or $/10^6Btu$) to electricity and steam generated within a power plant [56].

reported learning rates span a large range, even among different studies of a given technology. So how is one to choose an appropriate value (or values) for a particular study?

The most straightforward choice of a learning rate for a sub-section is the reported value for a technology that is identical or similar to one under study. For example, decomposing a coal-fired or gas-fired power plant will yield some sub-sections that directly correspond to commercial technologies with reported learning rates in Section 1.2.2.2. **In the case of an advanced technology with no historical data, prospective learning rates based on modelling studies may be available or must be estimated on some other basis.** For instance, advanced process designs may have attributes that resemble those of other current technologies (such as physical similarities, reactions, or physical/chemical processes)**.** For example, a study to estimate the future cost of power plants with CCS [26] argued that a post-combustion amine-based system for CO_2 capture closely resembled the basic design of a post-combustion wet limestone flue gas desulfurization (FGD) system for SO_2 capture. Thus, learning rates for FGD systems were used as a proxy for CO_2 capture technology (see Table C-2 in Appendix C). Other examples of learning rate assumptions based on analogies can be found in the literature (e.g., [57]).

In cases where an advanced technology has no suitable retrospective or prospective analogues to serve as a proxy for learning rates, two other options are available. One is to rely on expert judgments, as in the hierarchy also proposed by Thomassen et al. [29]. Table 1-2 includes examples of such estimates. The other option draws on some general characteristics of historical learning rate data for guidance. The first is that **the highest learning rates (e.g., 20–30 percent) are typically associated with smaller-scale technologies that are modular in nature and amenable to mass production**, such as solar cells and panels. In contrast, **learning rates are significantly lower for large-scale process systems and technologies that are typically field-erected and designed for a unique site or size** (such as power plant boilers, steam turbines, chemical processes, and air pollution control systems)**.** Such technologies typically have learning rates on the order of 10–15 percent. Thus, the type of technology under study can make a significant difference (a factor of two or more) in the value of an appropriate learning rate. In general, the lowest learning rates (on the order of 1–5 percent) are found for mature fossil fuel power plants using commercial technologies (see Section 1.2.2.2).

Another characteristic of the historical learning rate data is the significant variability often seen in the results across studies by different researchers using different data sources from different locations and different time periods. Because a variety of factors contribute to such results, the prevalent one-factor learning model can only approximate the expected outcome for a particular technology. Thus, the average learning rate from multiple studies is a reasonable best choice in such cases. However, **a thorough uncertainty analysis is indispensable in any application of learning rates** (see Section 1.6.1 below).

Finally, as noted above, **the choice of a learning rate also may depend on the purpose of the analysis and the questions or decisions it is intended to inform.** For example, if the objective is to obtain a conservative or upper-bound estimate of future cost, then a low value of learning rate, within a range of historical values, would be appropriate. In contrast, if the objective is to estimate a best-case or optimistic future cost, then a higher rate of learning would be appropriate. In the latter case, however, care must be taken to avoid assumptions that lie outside the range of historical experience for similar types of technology if the result is to be credible for a Type 2 (What Will) cost estimate.

1.5.4   Starting and end points for experience curves

As illustrated earlier in Section 1.2.3, the application of an experience curve using the hybrid method requires assumptions for when cost reductions begin and how long it continues at the specified rate. The guidelines for such assumptions depend upon the current maturity of the plant sub-section or technology in question, as explained below.

1.5.4.1   Guidelines for advanced (Pre-Commercial) technologies

Advanced technologies that have not yet been deployed at a commercial scale are the main focus of this report. For such technologies, the choice of a starting point for learning (denoted in Figure 1-8 by the point C1) depends on whether one or not the current (FOAK) cost estimate for a commercial-scale project would indeed be accurate were such a facility actually built. If so, this is the appropriate starting point for cost projections. If no other large-scale facilities have been built and operated, the size of this first commercial project would represent the cumulative installed capacity, C1.

However, historical experience for power plants and related technologies indicates that cost estimates, as well as actual costs, for FOAK projects or plant components often fall short of the actual cost required to achieve successful commercial operation. In many cases, this is because the process fails to perform as reliably or as well as expected. Many early FGD installations, for example, experienced corrosion problems, clogging, and poor SO_2 removal rates that resulted in unplanned outages and increased maintenance costs [14]. Only after improved—and much more costly—designs for the technology were built and operated successfully did FGD costs begin to fall along an experience curve. Similar experience has been found for other FOAK technologies [26].

The implication of these findings is that **there is a reasonable chance that the true cost of the first *successful* installation of a new commercial technology will exceed the FOAK cost estimate** above, even after allowing for the recommended process and system contingency costs. Thus, **a scenario approach is advised.** The most optimistic case is to assume that the FOAK cost estimate for a commercial plant is indeed accurate, that the facility operates and performs as expected, and that further cost reductions are achieved for all subsequent installations of the technology.

Alternatively, a more conservative approach is to assume that several large-scale facilities must be designed, built, and operated successfully before the estimated FOAK cost and performance for the advanced technology is actually achieved. In this case, learning does not begin until the installed capacity of the advanced technology has reached some minimum level, C_{min} (MW), a parameter of the analysis. In effect, this parameter compensates for insufficiencies in the FOAK cost estimate. A sufficiently high value of C_{min} also obviates the need to explicitly incorporate a system contingency cost factor for the first several installations.

General guidance for numerical estimates of C_{min} is to assume higher values for technologies that are currently at earlier stages of development and furthest from commercial demonstration. For example, in view of early experience with FGD, SCR, and other newly-deployed power plant technologies, IEAGHG [56] assumed starting points ranging from 3,000 MW to 10,000 MW for NGCC, PC, IGCC, and oxy-combustion power plants equipped with carbon capture systems. Alternatively, one could assume a certain *number* of plants of a given size to estimate the starting point capacity. In all cases, a delay in the onset of learning results in slower reductions in cost vs. cumulative capacity.

At the far right end of the cost curve, an assumption also is needed for the end point of the experience curve projection. If the objective of the analysis is to estimate the likely NOAK cost of the advanced technology **a definition is needed as to what constitutes the mature N^{th} plant.** The earlier discussion in Section 1.2.3.2, together with the illustration in Figure *1-4*, showed that the cost curve tends to flatten after about 15 to 20 replications of the initial capacity, based on the one-factor model for learning. For a mid-value learning rate of 15 percent, twenty replications (a little over four doublings) is also the point at which the cost falls to half its initial value. If this is taken to be the end point for the analysis of an advanced 500 MW power plant, the cumulative installed capacity would be 10 GW for the optimistic case where learning is assumed to begin after the first installation. If the onset of learning is delayed, the end-point capacity to reach a 50 percent cost reduction would be greater. Other studies assume that the cost of new technologies decline at different rates. The EIA National Energy Modeling System (NEMS) model, for example, optimistically assumes that learning begins immediately after the first installation of a new technology and that learning rates decline over three periods of cumulative capacity [58]. Additional details of EIA assumptions are shown in Section 1.6.1.2.

1.5.4.2 Guidelines for commercial technologies

Conceptually, starting points for learning (i.e., an estimate of the current installed capacity) also are required for plant sub-section technologies that are currently commercial and already in wide use. Common examples include PC and NGCC power plants to which an advanced technology, such a novel CO_2 capture system, is added. In these cases, however, precise estimates of total current capacity are not usually necessary because the incremental capacity of the new advanced technology is typically small relative to the current base of established technologies. This is illustrated in Table C-3, in Appendix C, which shows several hundred GW of initial capacity for PC and NGCC plants worldwide in the IEAGHG study [56]. Thus, a relatively large (e.g., 10 GW) increment of advanced technology capacity represents only a small percentage change in the total capacity of mature technologies, resulting in a small (often negligible) change in cost due to learning. In addition, mature plants also tend to have lower learning rates, which further contribute to small or negligible reductions in these sub-section costs. In such cases, it **can be assumed that the cost of mature plant sub-sections is unchanged by small increments of new capacity, obviating the need for an experience curve analysis.** (see Section 1.5.5 for a numerical example that illustrates this statement.)

In cases where a commercial technology has not yet reached maturity in a particular application (e.g., a power plant design employing coal gasification) several factors must be considered in estimating the current capacity of the technology to be used in the learning rate equation. One is the geographical scope for learning, specifically, whether it is based on regional, national, or global installations. This is important since **the broader the scope, the larger the initial capacity estimate. This, in turn, results in a smaller cost reduction for a specified increment of new capacity.** The guidance for this case is that **the geographic scope for current capacity estimates should reflect the scale at which learning occurs for the technology in question.** In most cases, this will be based on global installations, reflecting a world in which information and experience is widely shared, and multiple vendors compete for markets, so that all users of the technology benefit from learning and cost reductions. While this may not always be the case, it is the most prevalent model for technologies whose learning rates have been studied and quantified [59].

Another factor in estimating current capacity is the so-called "spillover effect" where experience with a technology in applications different from the one under study indirectly contributes to learning and cost reductions. Examples include the use of CO_2 capture systems and coal gasifiers in industrial processes as opposed to power plants. The addition of spillover effects further increases the initial capacity estimate, which again affects the magnitude of cost reduction for an additional increment of capacity. **In cases where the spillover effect is sizeable, estimates should be made of the "equivalent capacity" of installations that contribute to knowledge spillover**, based on an appropriate metric such as the volumetric gas flow treated. On that basis, the total equivalent capacity values shown in Table C-3, in Appendix C, were estimated (see Rubin et al. [26]). Absent such estimates, larger cost reductions for the advanced technology will be projected for a given increment of new capacity, based on the smaller initial value.

1.5.5 Projecting future costs

Once all sub-section learning rates and initial capacity values have been specified, Equation 1, shown earlier, is used to project future costs. The parameter, b, in Equation 1 is determined using Equation 4. A simple numerical example illustrates this calculation for a constant learning rate and an end-point capacity of 20 GW of an advanced process component added to a conventional (mature) power plant. Additional parameter assumptions and calculated values for this example are as follows:

Advanced Technology Sub-Section:

Assume: Current FOAK cost = $3,000/kW;   LR = 0.15; C_{min} = 1,000 MW; C_{final} = 20,000 MW

From Eq. 4: $b = \dfrac{-\log(1-0.15)}{\log(2)} = 0.234$

From Eq. 1: $y = \dfrac{(3,000)}{(20,000/1,000)^{0.234}} = 1488$ \$/kW (at the end point)

Mature Technology Sub-Section:

Assume: Current (initial) cost = \$1,000/kW;   LR = 0.05; $C_{initial}$ = 200,000 MW; C_{final} = 220,000 MW

From Eq. 4: $b = \dfrac{-\log{(1-0.05)}}{\log{(2)}} = 0.0740$

From Eq. 1: $y = \dfrac{(1,000)}{(220,000/200,000)^{0.074}} = 993$ \$/kW (at the same end point).

One sees in this example that after 20 GW of cumulative new capacity and experience the advanced technology component cost fell by 50%, whereas the maturity sub-section cost fell by only 0.7% because of its greater initial capacity as well as its lower learning rate. Figure C-1, Appendix C, shows additional results of this type.

While most published learning rates apply only to capital costs, projections for O&M costs and plant efficiency improvements follow the same procedure where learning rate data are available. At the end point of the analysis (or any intermediate point, if desired) the various sub-section costs are then summed to obtain the total capital and O&M costs of the plant.

Similarly, a levelised cost of electricity (LCOE) calculation can be performed at any point in the future capacity projection by introducing appropriate values of levelised capacity factor and fixed charge factor. These two parameters also change as a new technology matures: capacity factor is likely to increase as plant reliability and availability improve. The weighted average cost of capital, and thus the FCF, typically declines as risks decrease with increasing experience. These changes in parameter values can be modelled simply as a step change (or a set of step changes) at a particular point(s) rather than as a continuous function. For example, one recent study assumed financing rates change from high-risk to low-risk after 10 GW of experience with an advanced CO_2 capture system [3]. This is illustrated later in the example presented in Section 1.7.

A final step that is strongly recommended in any NOAK cost projection is an uncertainty analysis for key results. This applies equally to the hypothetical cases of Type 1 (What If) cost estimates. Section 1.6 below elaborates further on methods and guidelines for characterising uncertainty in advanced technology cost estimates.

1.6   Characterising uncertainty

Previously published cost guidelines remind us that cost estimates commonly reported as single (deterministic) numbers are actually the central value of a range or distribution of possible outcomes (e.g., -30% to +50% for an AACE Class 4 cost estimate) [16, 60]. While uncertainties are inherent in all cost estimates undertaken for technology assessments and screening (e.g., AACE Class 4 or 5, as defined in [43]), costs for advanced technologies that are not yet commercial have significantly greater uncertainty and/or variability. One recent study, for example, found that independent capital cost estimates for the same advanced carbon capture process for a coal-fired power plant differed by as much as 65 percent, mainly because of differences in equipment sising methods and sources of cost information [45].

The hybrid costing method described in this chapter introduces additional uncertainties associated with the learning curve analysis. Thus, it is important to recognize and characterize all major sources of uncertainty that affect the integrity and robustness of any advanced technology cost estimate. An uncertainty analysis also can help establish empirically-based bounds and expectations for future costs and potential cost reductions. This perspective is critical for effective R&D planning and management of early-stage technologies.

This section briefly reviews and illustrates some of the leading methods available to characterize uncertainties. They include both quantitative and qualitative methods that are discussed more extensively

in the literature, including sensitivity analysis, probabilistic analysis, and the use of expert judgments (e.g., [5, 61]). Readers should consult such resources to learn more about the methods highlighted below.

1.6.1 Sensitivity analysis

Sensitivity analysis is the most familiar and widely-used method of uncertainty analysis. Here we distinguish between two major types of sensitivity analyses: parameter uncertainty and model uncertainty. The first refers to changes in the parameter values of a particular calculation or mathematical model. The latter refers to changes in the underlying model and its parameters or variables. Further differentiations can also be made in the types of sensitivity and uncertainty analyses (see e.g., [5]).

1.6.1.1 Parameter Sensitivity

The most common method of analysing uncertainty is a "one-at-a-time" sensitivity analysis in which the value of a single parameter in a performance or cost calculation is varied from its nominal or base case value to quantify the effect on a result of interest, with all other parameters held constant. This is effectively a measure of the "local sensitivity" around the point determined by the nominal values of all parameters. Figure C-2, and Table C-4, in Appendix C, show two examples. Figure C-2 shows the sensitivity of total capital cost for an advanced power plant design to a range of learning rates applied to each plant sub-section, then summed to obtain the high and low estimates shown for the overall plant. Table C-4 shows another example in which each of seven additional parameters of an experience curve analysis are varied, in turn, from their nominal values with all other parameters held fixed. The results reveal which parameter uncertainties have the largest impact on capital and LCOE cost results.

Appendix D shows two additional examples from a study of baseline power plant costs using detailed engineering-economic models [43]. Figure D-1 shows the sensitivity of the LCOE to changes in the assumed prices of purchased fuels. Figure D-2 shows the results of a two-way sensitivity analysis in which a "phase diagram" reveals the sensitivity of the lowest-cost plant type to changes in two independent variables (in this case, the price of natural gas and the selling price of captured CO_2 for plants with CCS). Other studies show examples of plant performance sensitivity to technology design variables as well as to economic and financial variables (e.g., [62]).

In most studies, however, the choice of parameters that are varied, and results that are displayed, are based on the judgment and preferences of the authors. Seldom do studies *systematically* identify the most important variables affecting a particular result. Consequently, important parameters and correlations between factors may be overlooked.

The guidance in this regard is to **first identify the study results or model outputs that are most important, given the purpose and objectives of the study.** In the context of this report, that would typically include one or more cost measures for an advanced technology component or integrated facility (e.g., its capital cost, O&M cost, or total levelised cost per unit of product). It may also include important performance measures, such as the net plant efficiency (or heat rate), net capacity, annual power generation (for power plants), and a rate of CO_2 and/or other emissions.

Next, identify the model parameters or assumptions that have the greatest influence on those key results. This can be done by varying each uncertain parameter one at a time and then viewing the change in key results with all other parameters held constant. Figure *1-9* gives an example of such an analysis in which an engineering-economic model was used to calculate the LCOE of a power plant with an advanced CO_2 capture system. The tornado diagram reveals that the LCOE is most sensitive to three of the fifteen variables shown. Assumptions about these parameters thus merit particular scrutiny and justification if the cost result is to be credible.

**Sensitivity of LCOE (€/MWh, change from a base value of 102.56)**
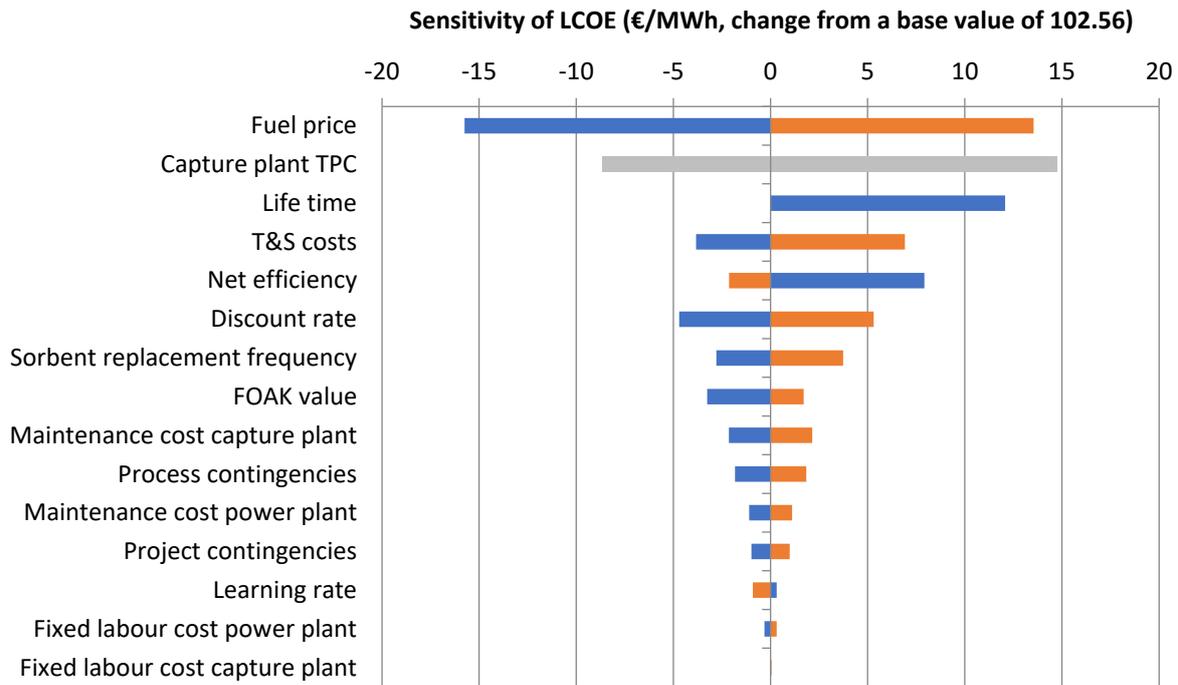
Figure 1-9. A tornado diagram indicating the change in levelised cost of electricity for a NGCC plant equipped with an advanced post-combustion CO₂ capture system [57]

Ideally, a comprehensive sensitivity analysis would systematically vary the nominal value of *every* model parameter by a fixed percentage (e.g., plus or minus 10%, subject to physical, thermodynamic, or other constraints) to first identify which variables have the greatest effect on key results. The values of parameters to which results are most sensitive should receive special scrutiny. Since some parameters may have greater uncertainty or variability than others, available data and judgments must be applied to estimate the overall uncertainty in key parameters.

In cases where a systematic sensitivity analysis is not practical (such as when using complex models with a great many variables), the judgment and experience of the analyst must be relied upon more heavily to identify the most relevant uncertain parameters. In such cases, a review of study results by an independent party can be helpful to flag any important omissions or issues. In many cases, other analysis methods may be needed to understand and characterize uncertainties more rigorously (see Section 1.6.2).

1.6.1.2 Model Uncertainty

Sensitivity analysis also can be used to characterize the effect of uncertainties in the underlying analytical models employed for techno-economic assessments, including the experience curve models discussed in Section 1.2.2.1. **In addition, models themselves can be varied to assess the effect of using different mathematical descriptions for (a part of) the model.** For example, while the log-linear model in Equation 1 is most commonly used for experience curves, other model formulations, such as the multi-factor regression models discussed in Section 1.2.2.1, or the piecewise and nonlinear models illustrated in Figure *1-10*, may better fit historical cost trend data in some situations. Thus, the data in Figure *1-10*(a) are best fit by a piecewise log-linear model with an initial learning rate of 7 percent, followed by a more rapid rate of 29 percent. Similarly, the exponential models in Figure *1-10*(b) indicate changing rates of learning that are believed to reflect a large initial deployment of new emission control technologies in response to new regulatory requirements, with little opportunity for learning until later generations of lower-cost systems were deployed [35].

(a)

(b)
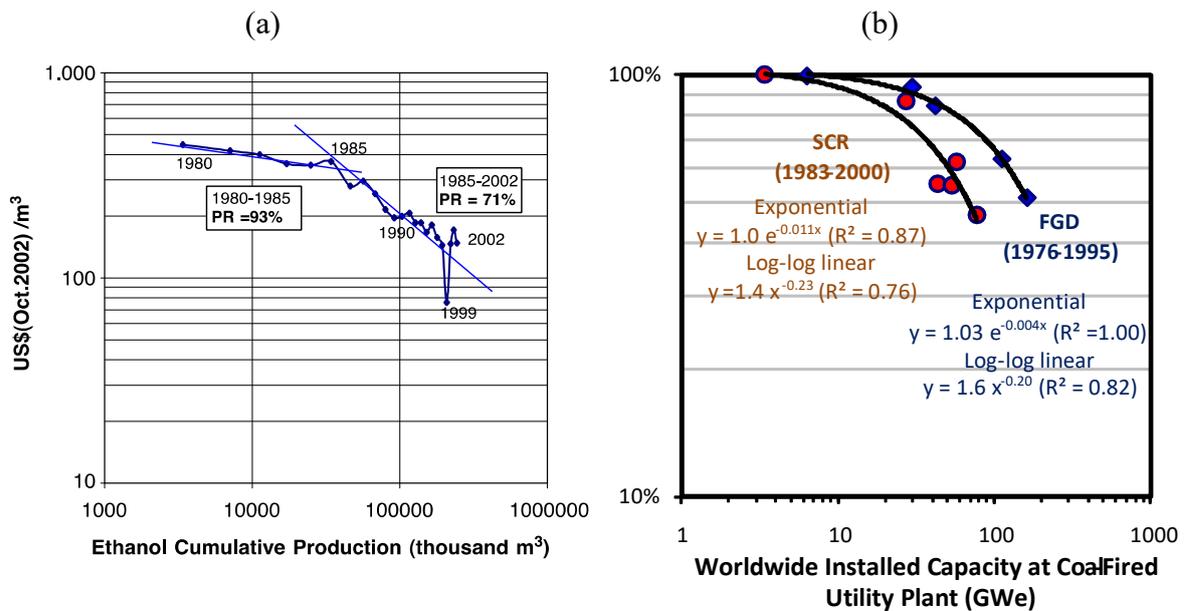
Figure 1-10. Examples of experience curves fit by (a) piecewise log-linear models with different learning rates and, (b) nonlinear exponential models [35]

A number of studies in the literature also suggest an S-shaped experience curve in which learning rates gradually decline as the technology matures and its cost approach a plateau (see Yeh and Rubin [35]). Declining learning rates for mature power plants also are assumed in the EIA NEMS model used for U.S. energy projections [58]. For designated "revolutionary" technologies (which include CCS, fuel cells, offshore wind, solar thermal, and others) an initial learning rate of 20 percent is assumed for the first three doublings of capacity, followed by an "evolutionary" stage with a learning rate of 10 percent for the next five doublings. This is followed by the "mature" stage with a learning rate of just 1 percent [59]. Figure *1-11* compares the resulting capital cost trajectory to that for three constant learning rates. One sees that after a rapid initial decline, the cost decreases more gradually; after eight doublings of the initial capacity (off-scale in this exhibit), it plateaus at approximately 30 percent of the initial cost. Table E-1, Appendix E, provides additional details of EIA learning rate assumptions for different power plant technologies.
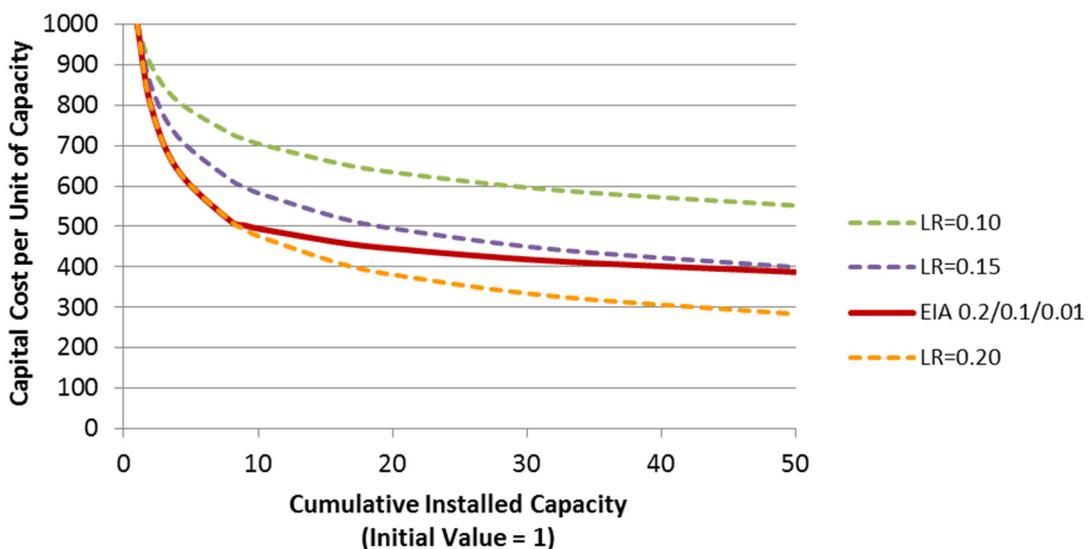
Figure 1-11. Capital cost trajectories for three constant learning rates plus the EIA/NEMS trajectory for a "revolutionary" technology with decreasing learning rates over three periods.

Yeh and Rubin [35] present a more complete discussion of learning rate uncertainties. **Since technological learning is a key element of the here proposed hybrid costing method, analysts conversant with this**

53

literature may wish to extend sensitivity studies to include alternative learning model formulations relevant to the technology of interest, in addition to the parametric variations discussed earlier.

1.6.2 Probabilistic analysis

While local sensitivity analyses are useful to understand how technology cost estimates are affected by changes in key assumptions and design parameters, the large number of variables involved in many cost estimates makes it impractical to study the effect of all parameters comprehensively. More importantly, a simple one-at-a-time sensitivity analysis overlooks the combined effect of interactions among multiple parameters, each with its own uncertainty or variability. Nor does it reflect global uncertainties over the full solution space, or provide any insight into the likelihood of a particular result, which can be especially important for answering 'what will' type of questions for technology-related decision-making. A probabilistic analysis addresses many of these shortcomings.

Rather than having a single (deterministic) value, uncertain parameters are quantified as a probability distribution function (PDF) specifying the likelihood of a different value occurring. Figure *1-12* shows an example from a project cost analysis, displayed as both a PDF (red bell-shaped curve) and a cumulative probability distribution (CDF, the thin black line) [47]. From such data, one can calculate other results of interest, such as the 90 percent confidence interval shown in the figure, or other global sensitivity indicators (similar to the tornado diagram in Figure 1-9, but calculated from results of a global uncertainty analysis; see [5]).
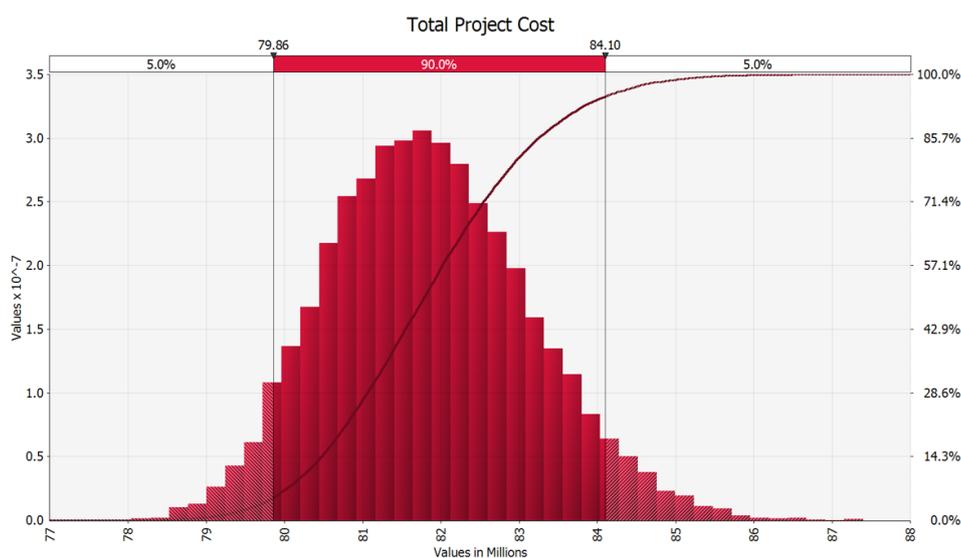
Figure 1-12. Example of a probabilistic cost distribution generated by risk estimating procedures [47]

Since few models allow direct analytical solutions of probabilistic problems, models with one or more uncertain parameters employ Monte Carlo or other efficient methods of repeated sampling of input parameter values to generate a range of numerical results that can be displayed either as a PDF or as a CDF, such as in Figure 1-13. In that example, a detailed techno-economic model was used to calculate the hypothetical NOAK cost of a power plant employing a novel ammonia-based system for CO_2 capture [63]. Probability distributions were assigned to 22 model input parameters including ten performance-related parameters, ten cost parameters, and two financial and plant utilization parameters (see Table D-3 in Appendix D for details). Figure 1-13 shows the overall uncertainty distribution for the resulting LCOE, as well as the cumulative contributions of different parameter groups. Also shown (as a vertical line) is the deterministic base case value. Its intersection point with the cumulative probability distribution reveals a 20 percent likelihood that the true cost is less than the nominal value - thus, an 80 percent chance it *exceeds* the nominal value based on the given parameter uncertainties (Figure D-1). These results show

skewed distributions for all parameter groupings, indicating a high probability that the LCOE will exceed the deterministic estimate.
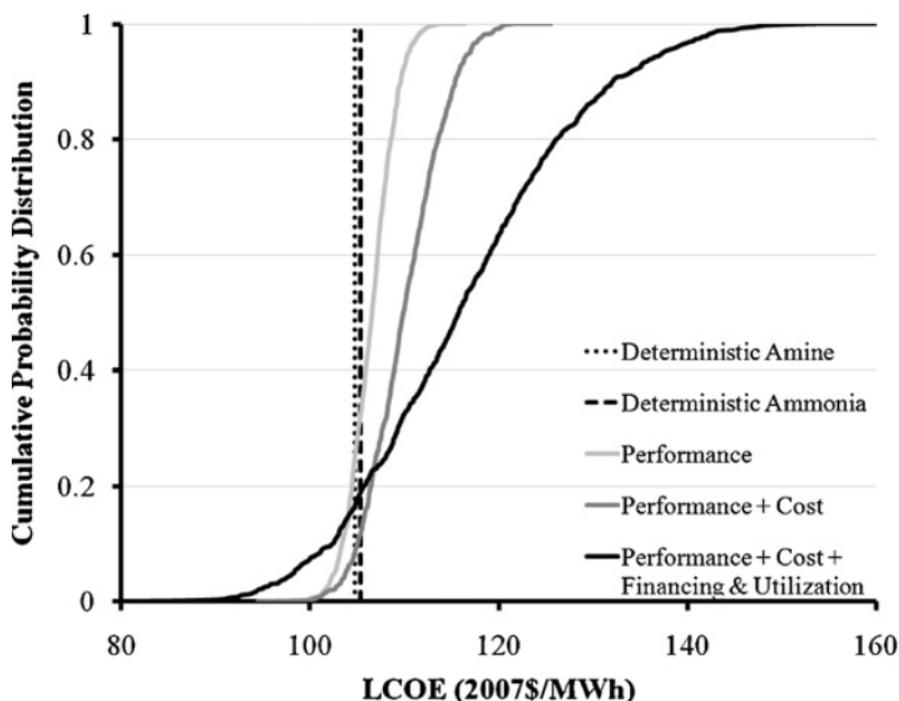
Figure 1-13. Cumulative probability distribution of LCOE for a PC plant with an advanced post-combustion CO_2 capture system. The figure shows the contribution of different parameter groups to the overall uncertainty [63]

Results such as this yield quantitative estimates of the cost and performance risks, as well as potential benefits, of an advanced technology. **A probabilistic analysis also can help identify the sources of greatest risk and the measures needed to reduce or eliminate those risks** via changes in process design, system design, and plant operation. As with sensitivity analysis, however, a comprehensive analysis of all uncertain parameters may be impractical for complex models that have a very large number of variables. In such cases, a screening analysis, together with the expert judgment of the modeler, must be relied upon to select the most relevant parameters. The ability to conduct such an analysis also requires software tools that are now widely available commercially, or analytical modelling tools that incorporate a probabilistic analysis capability (e.g., [38]). It also requires a deeper understanding of the uses and limitations of probabilistic methods than can be presented here. Other readings are recommended for additional background (e.g., [5, 38]).

A final topic for discussion is how **to** quantify the uncertainty or variability in a particular model parameter. Key to the quantification of uncertainty or variability is the availability of empirical data for the parameter of interest, as well as knowledge of physical or thermodynamic limits. Empirical data offer the most rigorous approach and is most applicable to parameter variability. This refers to measurements of technology characteristics and performance parameters, as well as data on the magnitude and variability of economic and financial parameters. In other cases, a value for true uncertainty may be set by physical or thermodynamic limits on the maximum or minimum value of a parameter used in a technology performance and cost estimate (e.g., a minimum work value for a chemical separation process). Lastly, the use of expert judgments is often required for parameter and uncertainty estimates where empirical data are lacking, or for estimating the future values of key parameters. The following section elaborates briefly on the latter topic.

1.6.3 Expert judgments

In the absence of empirical data, cost and uncertainty estimates for advanced technologies rely heavily on the use of expert judgments, both for Type 1 (What If) and Type 2 (What Will) studies. Methods and protocols for expert elicitation have been widely employed to estimate various types of uncertainties when data are lacking. In the context of this report, two major questions of interest are: what values can be usefully obtained via expert elicitations, and how exactly are those values obtained?

Expert judgments are commonly used in FOAK cost studies to estimate the current cost of an advanced technology component or a material that has not yet been fabricated and produced commercially. They also are used in What-If studies to obtain quantitative estimates of the expected future cost of a current or advanced technology, often for the purpose of assessing the potential economic and/or environmental benefits of an R&D program in a particular time frame [64]. Experts also are asked to quantify the likely future value and uncertainty of key technical and economic parameters used to calculate future technology costs. Figure 1-14 shows an example from such an elicitation used to obtain parameter values and uncertainty distributions for an engineering-economic model used to calculate the performance and cost of an amine-based CO_2 capture technology [65]. More recently, expert judgments provided a set of *qualitative* indicators for a "pedigree analysis" to assess the strength and quality of data inputs for advanced technology cost estimates [5, 66].
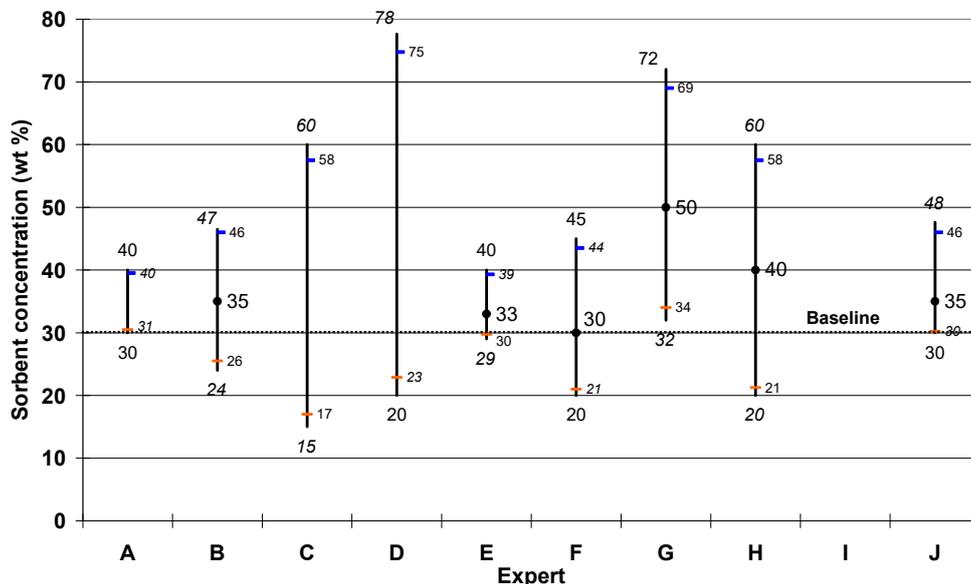
Figure 1-14. Elicited judgments from ten experts for the sorbent concentration in commercial amine systems ten years in the future assuming modest growth in R&D. Each distribution shows the nominal value (dot), range (vertical line), and 90 percent confidence interval (small cross lines) [65]

Methods to obtain expert judgments vary widely. **The most rigorous method of expert elicitation follows a detailed protocol** requiring significant time and effort in the selection of experts, the preparation of appropriate background materials and questions, and the elicitation of subjective probability distributions from in-person interviews with each expert [67]. Other studies have employed written correspondence supplemented by personal and/or telephone interviews. The data in Figure 1-13, for example, were elicited from a set of experts in five different countries working in industry, academia, research organizations, and consultancies. Care was taken to formulate questions in a manner informed by expert elicitation research. Other cost studies, however, employ more informal, less structured methods of eliciting expert judgments, such as drawing upon co-workers in an organization. Depending upon its purpose and scope, the results of such elicitations may be viewed as less rigorous than a more encompassing analysis. Thus, **analysts employing expert judgments in advanced technology cost estimates should be well-grounded in elicitation methods and pitfalls** (e.g., as discussed in Morgan [67]).

1.7 Illustrative example of a hybrid cost model analysis

To illustrate how the proposed hybrid method might be used to assess the expected future cost of an advanced technology, a simple example of a hybrid cost model analysis is presented based on a study of a new 550 MW coal-fired power plant with post-combustion CO_2 capture using an advanced polymeric membrane system with sweep gas recycle of captured CO_2 [3]. The advanced plant design was taken from an earlier study [10] that used engineering-economic models to estimate the NOAK cost goal of the plant assuming that the bare erected cost of the membrane-based CO_2 capture module achieves a cost goal equivalent to $80/m^2$ of membrane material (in 2007 dollars). The remainder of the supercritical power plant and its emission control systems were assumed to be mature commercial technologies with known costs. This study represents a typical Type 1 (What If) cost analysis.

The objective of the hybrid cost model analysis was to answer typical Type 2 (What Will) questions: Based on its current state of development, what will the actual (projected) NOAK cost of this advanced technology be? How does that compare to the NOAK cost goal in the NETL study? Based on historical experience with technology cost reductions, how many plants (with how much installed capacity of the new carbon capture technology) would it take before the NOAK cost goal could be met? What is the uncertainty in these estimates for the optimistic case where the first full-scale installation of the advanced technology performs as expected? What are the major sources of uncertainty in this analysis?

As noted earlier in this chapter, an analysis to address these questions can be undertaken at various levels of detail. The approach in this example was to expend a minimum level of effort and resources to obtain preliminary results that could be refined later if initial findings warranted a greater effort. Accordingly, a number of simplifying assumptions were made, as outlined below.

First, in the absence of reported data on the actual current cost of the novel membrane material described in the NETL [10] study, the FOAK cost estimate for the hybrid model study assumed the NETL "near-term" capital cost goal equivalent to $150/m^2$ of membrane material as a lower (optimistic) estimate. A higher (more conservative) capital cost of $250/m^2$ was assumed as a sensitivity analysis for this preliminary assessment. The latter value assumes that production scale economies for a full-scale (550 MW) FOAK plant can achieve a cost well below the current cost range of approximately $500/m^2$ to $750/m^2$ reported for smaller-scale industrial membrane systems [68]. Based on the current level of development for the advanced membrane capture system reported by NETL [10], the process contingency cost factor was set to 35 percent, compared to 20 percent in the NETL study. All other plant costs were kept at the NETL study values.

For O&M costs, the membrane replacement material for the FOAK plant was assumed to have a higher unit cost (proportional to its capital cost) and a 20% shorter lifetime relative to the NOAK assumptions. For calculating the LCOE, the capital charge factor was set at NETL's high-risk value for the first 10 GW of installed capacity (about 20 plants), then reduced to the commercial (low-risk) value for subsequent projects. In the absence of historical data for membrane-based learning rates, the learning rates for capital and O&M costs of the post-combustion membrane-based system for CO_2 capture were based on those for post-combustion capture of SO_2 (Table 1-1). For this analysis, learning was assumed to begin after the first installation of the advanced system, consistent with the study objectives noted earlier. Learning rates for the remainder of the supercritical PC plant were assumed to be small, with a negligible reduction in balance-of-plant cost over the projection period of 40 GW of new capacity for the advanced technology (see illustrative calculation in Section 1.5.5).

Figure 1-15 shows the results for total capital requirement of the overall power plant as a function of increasing deployment of the advanced technology for the two estimates of FOAK cost. The NETL NOAK cost goal, called Case 5A, is shown as a horizontal dotted line. The graph shows that achieving that goal for the lower FOAK cost would require about 20 GW of installed capacity (approximately 40 installations) of commercial experience with the advanced membrane technology. For the higher FOAK cost estimate about 80 GW of cumulative capacity (off-scale in Figure 1-15) would be required.
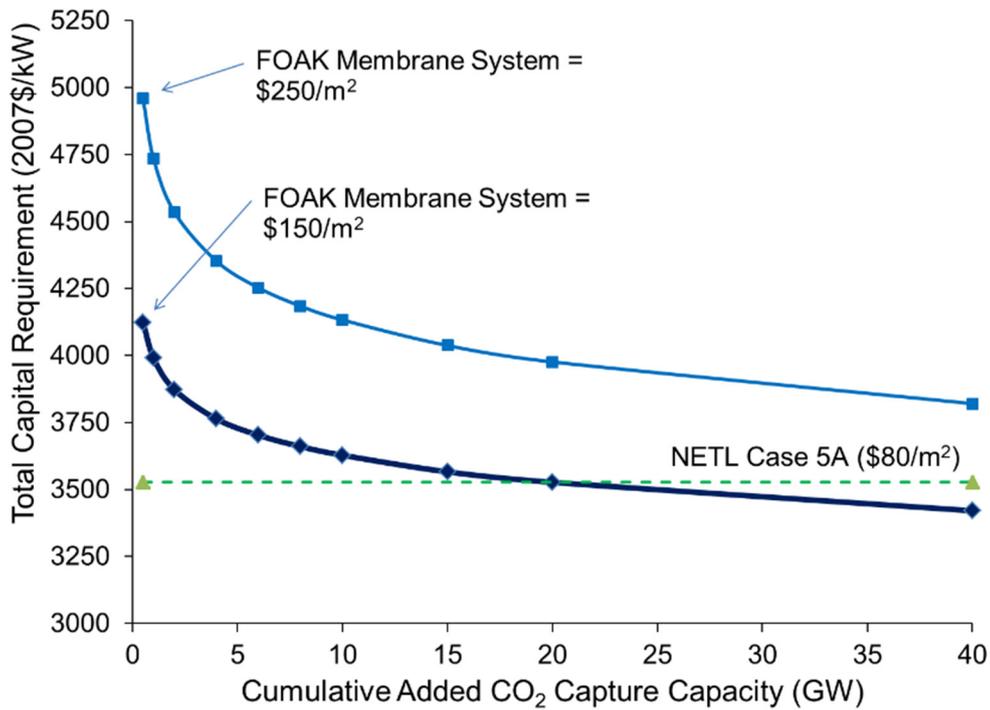
Figure 1-15. Total power plant capital requirement for the high and low FOAK cost estimates of the advanced membrane-based CO₂ capture system. Also shown is NOAK cost (NETL Case 5A) meeting the membrane system cost goal of $80/m² [3]

The cost trajectory for total annual O&M cost of the plant (not shown) follows a qualitatively similar path as in Figure 1-15, albeit with a higher learning rate for the advanced capture system, again based on FGD experience (Table 1-1). Figure 1-16 then combines all capital and O&M costs with additional assumptions for plant financing and utilization to show the constant-dollar levelised cost of electricity for the two cases.
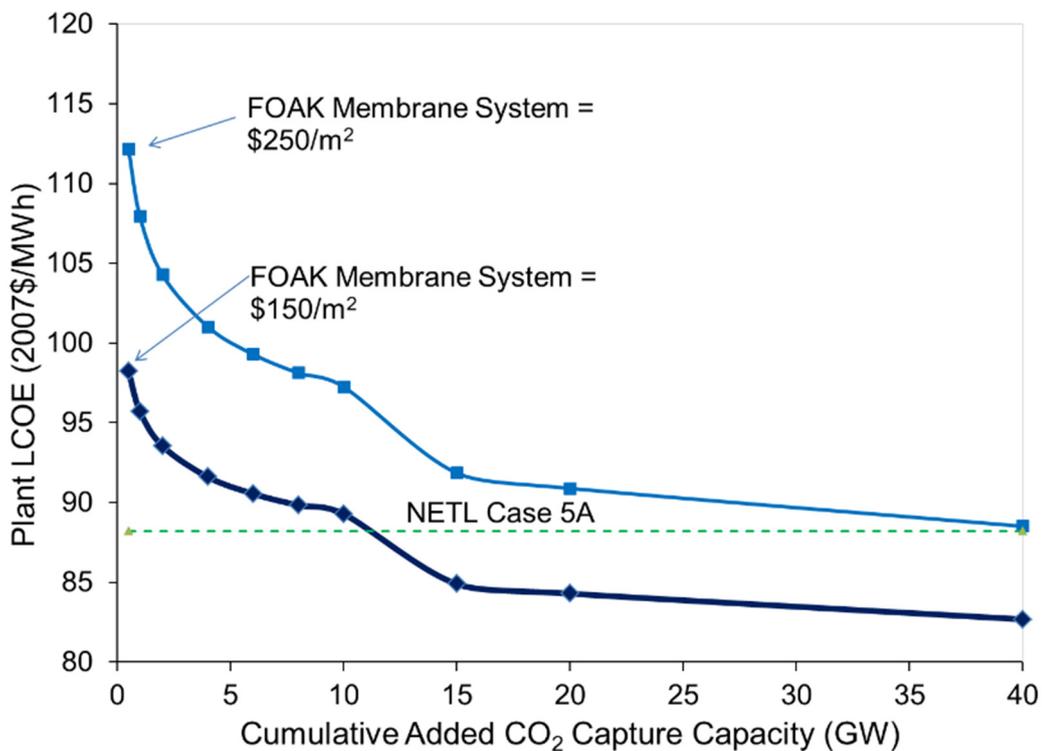
Figure 1-16. Levelised cost of electricity (LCOE) for the two values of FOAK membrane module cost. Financing change from high-risk to low-risk after 10 GW of capture system experience [3].

58

The decline in LCOE is seen to be more rapid after 10 GW of capture capacity experience due to the assumed reduction in risk and financing charges at that point. For the lower FOAK cost estimate, the advanced plant would require about 12 GW of experience (about 24 installations) to reach the NOAK LCOE cost goal (NETL Case 5A). For the higher FOAK cost, substantially more experience (over 40 GW of capacity) would be needed to reach the Case 5A target. NETL Case 5A also assumed a high-risk cost of capital (inconsistent with the premise of a mature NOAK plant). The more appropriate low-risk (commercial) cost of capital would lower the LCOE for Case 5A and thus further increase the cumulative capacity needed for the advanced plant design to reach the NOAK cost goal.

The addition of uncertainty in the learning rate assumptions for this example would further broaden each line in the above figures into a band similar to the one shown in Figure C-2 (Appendix C). In turn, this would further broaden the estimated uncertainty in the projected NOAK cost of the advanced technology. This is illustrated in Figure 1-17, which compares the NOAK capital cost goal in the NETL study to the FOAK cost and the projected "actual" NOAK cost from the hybrid cost analysis. In this illustration, the nominal learning rate of 11% for the membrane-based capture system is varied from 7% to 15%, and the Nth-of-a-kind plant is assumed to be reached after five doublings of the initial capture system capacity (in this case, about 18 GW). Note that because the CO_2 capture system accounts for only a fraction of the total plant cost, with little or no reduction in the rest of the plant cost, the percentage reductions in overall cost seen in this example are much smaller than the reduction in capture system cost.
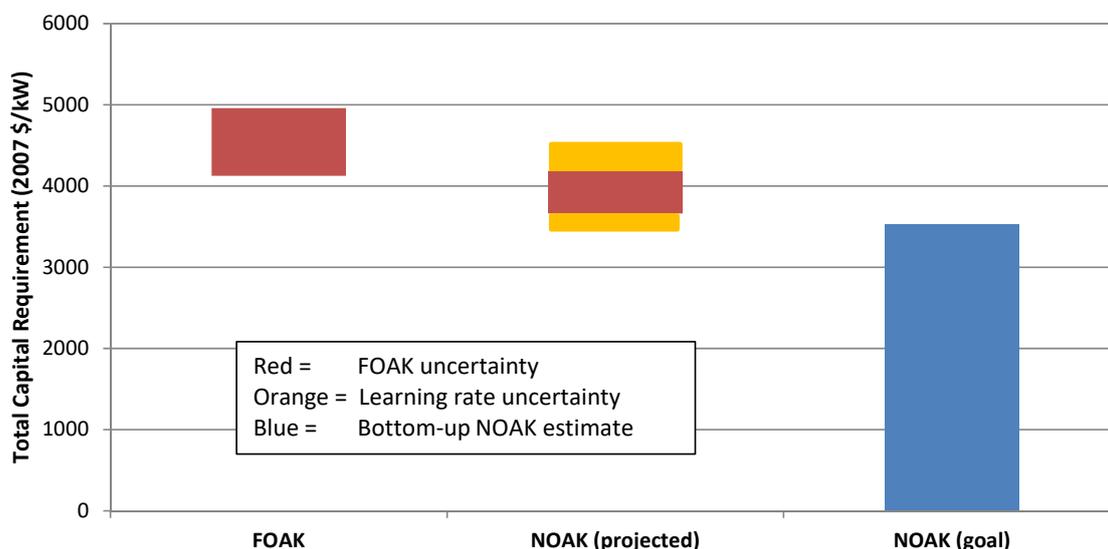
Figure 1-17. Comparison of the total power plant capital requirement for the FOAK plant, projected NOAK plant, and NOAK cost goal including uncertainty in FOAK cost and learning rate for the advanced membrane technology.

Figure 1-17 shows that under the assumptions of this analysis the uncertainties in FOAK cost and capture system learning rate both contribute significantly to the overall uncertainty in projected NOAK cost. Overall, these results indicate that the actual NOAK cost is likely to be significantly higher than the NOAK goal of the bottom-up (What If) cost estimate.

As noted earlier, there is considerable scope to further refine and expand the uncertainty analysis to incorporate additional variables of both the hybrid cost model as well as the engineering-economic model used to generate the NOAK goal. As always, the value of further refinements depends strongly on the purpose of the cost estimate and the decisions or judgments it will be used to inform. In this case, additional efforts to refine the estimated FOAK cost of the advanced membrane module (e.g., via vendor quotes) would be especially helpful given the importance of that estimate for NOAK cost projections.

1.8 Discussion and conclusion

This chapter has presented a framework for estimating the future "N^{th}-of-a-kind" (NOAK) cost of advanced technologies that are currently at early pre-commercial stages of development. That framework distinguishes between two types of question that commonly motivate such a cost analysis: "What If" questions about the hypothetical cost of a technology that meets specified R&D goals; and "What Will" questions regarding the actual expected cost of an advanced technology once it is mature.

The latter type of question is of particular interest because of the shortcomings in current methods for estimating the expected NOAK cost that were identified in this chapter, as well as the ambiguity in many cost studies as to the meaning of reported NOAK costs. Indeed, the first conclusion drawn from this study is that there is a need for greater clarity as to the question a reported NOAK cost result is intended to answer. Going forward, **we recommend that authors of cost studies use the term "NOAK goal" or "aspirational NOAK" when conducting "What If" studies, and the term "expected NOAK" or "projected NOAK" when reporting "What Will" estimates of the future cost of an advanced (pre-commercial) technology.** While some authors may prefer to use other adjectives (including "what if" and "what will"), the term NOAK should not be used in isolation without a clear descriptor.

Regarding "What Will" cost estimates for advanced technologies, the hybrid costing method described in Section 1.2.3, which combines a "bottom-up" engineering-economic analysis with a "top-down" model of technological learning, offers an approach to address the identified deficiencies in current methods. The hybrid cost analysis focuses new attention on the current (first-of-a-kind) commercial cost of an advanced technology. Methods and assumptions for estimating FOAK plant costs vary significantly from those for known commercial technologies, as discussed in Section 1.4 of this report. **A bottom-up FOAK cost estimate is recommended as the starting point for projecting future cost reductions of advanced technologies based on historical experience with similar or related technologies.** This is embodied in the application of technology experience curves and historical learning rates that underscore the importance of cumulative experience in plant deployments and operation (together with other factors) in achieving future cost reductions. Methods for implementing these cost models were elaborated in Section 1.5.

As with traditional cost analyses, a variety of tools and methods are available to also characterize uncertainties in cost results and the influence of key decision variables. Three methods - sensitivity analysis, probabilistic analysis, and expert judgments - were discussed and illustrated in this chapter. **An uncertainty analysis is especially important for FOAK and projected NOAK costs for advanced technologies** because of their intrinsically greater uncertainty compared to well-established commercial technologies. Uncertainty analysis also is important in calculating aspirational NOAK cost goals since these also depend heavily on assumptions and judgments that may vary considerably.

This chapter represents an initial effort to identify needed improvements in current costing methods and to provide guidance for future cost studies, especially for advanced (pre-commercial) technologies. Continuing efforts also are needed to further develop the models, databases, and guidelines that support applications of the hybrid costing method. This includes methodological improvements and quantitative guidelines to improve the development of FOAK cost estimates and reduce the uncertainties in projected NOAK costs for advanced technologies. Despite current limitations, however, the hybrid modelling approach can enhance prevailing assessments of advanced technologies by providing new insights regarding the time frame and requirements for their cost-competitiveness with existing or other advanced technology concepts. Further applications of the hybrid method can thus begin to offer a more complete and realistic approach to assessing the economic potential of advanced energy, industrial and environmental systems, and priorities for R&D management.

Chapter 2 : Towards improved cost evaluation of carbon capture and storage from industry[7]

2.1 Introduction

2.1.1 Carbon capture and storage from industry

The industry sector accounted for over a quarter (9 GtCO$_2$) of direct global CO$_2$ emissions in 2019 [69][8]. If indirect emissions (i.e. emissions arising from power and heat demand) are included, this sector is responsible for nearly 45% (16 GtCO$_2$) of global CO$_2$ emissions. Despite the historic decline in CO$_2$ emissions in early 2020, caused by the Covid-19 crisis, direct industrial CO$_2$ emissions are expected to rebound as economic conditions improve and continue to grow to around 10 GtCO$_2$ in 2060 [70]. Reducing industrial CO$_2$ emissions presents several challenges. One-third of industry energy demand is for high-temperature heat, for which there are few mature and affordable alternatives to the direct use of fossil fuels [71]. Process emissions, accounting for one-quarter (almost 2 GtCO$_2$) of industrial emissions, result from chemical reactions and therefore cannot be avoided by switching to alternative energy sources [71]. Last, industrial facilities are long-lived assets, leading to potential "lock-in" of CO$_2$ emissions for decades to come. Carbon Capture and Storage (CCS) retrofit is the only technology able to address these challenges and achieve deep emission reductions across the industry sector.

The three highest-emitting industry subsectors in 2019 were iron and steel (2.6 GtCO$_2$), cement (2.4 GtCO$_2$), and chemicals (1.4 GtCO$_2$), together responsible for 70% of industry's direct CO$_2$ emissions [69]. The complementary share of industrial emissions originates from multiple industrial activities, such as pulp and paper, aluminium, textile, food, and beverages, etc. Industry and fuel transformation (hereafter jointly referred to as "industry") represents a wide variety of processes and CO$_2$ point sources. Among these emitters are high-purity CO$_2$ sources (e.g. natural gas processing, bioethanol production, and hydrogen production), which provide low-cost opportunities for CCS. Furthermore, although some subsectors currently represent a "small" share of global emissions, they may grow rapidly over the coming decades. For example, increased hydrogen production is expected to be a key strategy to decarbonise heat and transport, as well as industrial emissions in certain sectors [71, 72]. Similarly, the waste-to-energy sector is on the rise as both, a waste management option and a heat and power production means [73].

Consequently, the momentum for CCS from industrial sources has accelerated around the world over the past decade [74]. This is especially the case in Europe due to the ambitious mitigation targets of the European Commission to reach carbon neutrality by 2050 [75]. Today, globally 20 large-scale CCS applications at industrial facilities[9] have entered in operation, while some 24 future large-scale applications are currently at different stages of development [76]. Among these, the Norway full chain project, Longship, is worth mentioning as it will include the first large-scale CCS project in the cement industry and potentially in a waste-to-energy facility[10]. It is worth noting that several of the projects have

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[7] This chapter was authored by Simon Roussanaly, Niels Berghout, Tim Fout, Monica Garcia, Stefania Gardarsdottir, Shareq Mohd Nazir, Andrea Ramirez, and Edward S. Rubin. It corresponds to a post-print version of the paper, "Towards improved cost evaluation of Carbon Capture and Storage from industry." International Journal of Greenhouse Gas Control 106, 103263. 2021" published under a Creative Commons license CC BY and is available in open access at https://doi.org/10.1016/j.ijggc.2021.103263. The corresponding author for this chapter is Simon Roussanaly (e-mail address: simon.roussanaly@sintef.no).

[8] Note that the 9GtCO$_2$ emission number reported by IEA [69] for the industry sector does not include activities related to fuel transformation such as, ethylene oxide, ammonia, and hydrogen production. In the present study, CCS for non-power applications from both industry and fuel transformation is discussed.

[9] An application corresponds to the implementation of CCS from a given industrial plant, which means that a CCS project considering a cluster of industries is considered here as multiple applications.

[10] Status in December 2020

been driven by demand for CO_2 for EOR operations. The capture and use of CO_2 for other purposes than long-term storage (e.g., as an input to the production of fuels, chemicals, and building materials) may also grow over the coming years [77].

2.1.2   Towards improved cost estimates for CCS from industry

To support CCS deployment, extensive studies assessing the techno-economic feasibility of CCS from industrial sources have been published, for example, on: iron and steel [78], cement [79, 80], refineries [81], pulp and paper [82], chemical production [83], oil and gas production and natural gas processing [84, 85], and hydrogen production [86]. Appendix F and the supplementary information provide an overview of selected publicly available, transparent, and detailed techno-economic studies for different industrial sectors including key characteristics, assumptions, and results. Although similar capture technologies can be considered in the case for power and industrial applications, their implementation can differ considerably by sector and industrial facility. This is due to differences in, among others, size and properties of the industrial process and gas streams (e.g. CO_2 partial pressure), plant layout (e.g. number of point sources and space availability), and energy supply options for the capture process, including the availability of low-value waste heat. Table 2-1 presents typical key plant characteristics for a wide range of industrial processes together with their status on number of existing and planned large-scale CCS deployment.

Different assumptions about these factors are partly responsible for the wide differences in cost estimates for CCS reported in literature, even within a given industrial sector [87, 88]. However, a significant part of the wide ranges in costs reported might arise from other factors, including differences in methodological framework [89], input data quality, cost metric definition, assumptions regarding capture technology maturity, retrofit vs. new-built facilities, plant location, energy prices, waste heat availability, and the inclusion (or exclusion) of CO_2 transport and storage. For example, different heat and power supply strategies may be selected resulting in very different CO_2 avoided cost [80, 90]. Furthermore, while CCS retrofit of existing facilities is considered to be an important mitigation measure to decarbonise long-lived assets [81], many studies only consider CCS for new-built facilities or underestimate the cost impacts of retrofitting.

A better understanding of the costs of CCS from industry is therefore needed to better inform decision-makers on the economic potential of CCS and guide research activities to improve the performance of promising options across industrial sub-sectors. Building on a previous CCS costing guideline papers [6], *the present work aims to contribute to the development of improved guidelines for cost evaluation of CCS from industrial applications*. In particular, the present guideline aims to support the establishment of improved cost evaluation of CCS from industrial applications through three key areas. The first area focuses on cost metrics and challenges that might arise in the case of CCS from industry. The second area focuses on three key underlying cost items for the evaluation of CCS from industrial plants: cost and CO_2-footprint of heat and power consumption; costs associated with implementation of CCS on a retrofit basis, and cost associated with CO_2 transport and storage. Finally, the last area focuses on transferability of data, experience, and maturity of CCS from power generation to CCS at industrial sources.

Table 2-1. Overview of characteristics of key industry subsectors

Industrial subsector	Indicative contributions to global CO_2 emissions [%] [69][a]	Indicative range of CO_2 emissions from a plant [MtCO2/y]	Indicative range of CO_2 concentrations [%vol]	Large-scale CCS applications at industrial facilities[b] [-] [76]	
				Existing	Planned[c]
Cement	7 (2019)	0.7-1 [79, 91]	14-33 [92]	-	2[d]
Iron and Steel	7 (2019)	2-14 [78]	4-27 [78]	1	-
Oil refining[e]	2 (2017)	0.7-2.4 [93]	8-20 [93]	1	4
Chemicals	4 (2019)	Various[f]	Various[f]	4	11
Natural gas processing	2.5 [94]	0.5-9 [95]	0-70%[g]	11	2
Hydrogen	2 (2018)	0.15-1.3 [86, 93, 96]	15-60%[h] [86]	3	5
Pulp and Paper	1 (2019)	1.3-2.2 [82]	10-25 [82]	-	-
Offshore oil and gas operations[i]	1.5 [97]	0.3-0.6 [98]	3-4 [85]	-	-

[a] As it is difficult to obtain contribution data for the same year, the numbers from IEA (2020b) also include the year, in parenthesis, corresponding to the indicative contribution. In addition, it is difficult to obtain numbers fully separated between hydrogen and chemicals as well as NG processing, hydrogen, and oil and gas extraction. There may thus be overlap between the numbers here presented for these industry subsectors.

[b] When CCS from a cluster of industries exist or is planned, CCS from each of these industries is here reported individually.

[c] Various level of development are here accounted for (early development, advanced development, completed)

[d] Note that one of these cement plants correspond to the Norwegian full chain CCS project which may also include CO_2 capture from a waste-to-energy plant.

[e] Hydrogen production units are excluded.

[f] Due to the multitude of industries under this umbrella, it is difficult to provide a meaningful range.

[g] Considering gas field that reached the production stage.

[h] Depending on hydrogen production technology (steam-methane reforming or autothermal reforming) and considered capture location.

[i] Emissions related to heat and power production offshore.

2.2 Cost metrics

Performance metrics and benchmarking are key aspects of technology selection, development, deployment, and improvement. They allow to identify apparent performance gaps and explanatory factors for these as well as best practices that lead to superior performance. Most performance metrics for capture systems are directly derived from power systems. Typical examples are investment costs, incremental products costs, cost of CO_2 captured, and cost of CO_2 avoided. These costs can be reported in absolute (e.g. Euro) or normalized terms (Euro per tonne CO_2 avoided or tonne CO_2 captured). Absolute costs are difficult to understand and interpret by non-experts. Without specific background knowledge it is difficult to know whether a given investment value is high or low. Normalized values, i.e., indicators that relate total costs (or investment) to output (e.g., tonne CO_2 captured, tonne CO_2 avoided, tonne of product(s), increase in production cost of industrial product) or input (e.g. per MJ fuel input) are often used as they allow (under similar assumptions) to compare and/or benchmark technologies.

2.2.1 Common metrics

The most common metrics to evaluate CCS are *cost of CO_2 captured* and *CO_2 avoidance cost* (also referred to as cost of CO_2 avoided) [6]. The former provides insights into the investments and operating costs associated with the CO_2 capture (or the CCS chain) while the latter gives insights into the performance of the capture unit (or the CCS chain) as a carbon mitigation option. *Cost of CO_2 captured* (Euro per tonne of CO_2 captured) relates the costs needed for building and operating the capture and compression units (or the whole CCS chain) to the physical amount of CO_2 captured and compressed from a given point source. Note that in most cases, CO_2 captured costs do not include the costs of transport and storage. Nor does it consider the CO_2 emitted from process energy supply. *CO_2 avoidance costs* (euro per tonne of CO_2 avoided) is the most common and meaningful metric used when assessing the costs of CCS as an abatement option as it provides insights into the costs of not emitting one tonne of CO_2 to the atmosphere while still producing a unit of useful product[11]. Therefore, it can be used to compare different types of CCS systems when assessing the most effective option to reduce CO_2 emissions from a given process. Note that the design of a capture unit, a compression unit, or a pipeline is based on the amount of emissions captured not avoided.

CO_2 avoidance cost (CAC) is a relative metric and therefore it requires a reference system (see equation 7). For the result to be rigorous, it is important that the industrial facility produces the same amount of key material output for both systems (with CCS and without CCS). Furthermore, CAC takes into account that operating the capture and compression unit requires energy and materials thereby producing additional indirect CO_2 emissions. In general, an industrial plant captures more CO_2 than it avoids, and therefore the costs per tonne of CO_2 captured are lower than the costs per tonne of CO_2 avoided.

Three different calculation methods can be used to evaluate the CAC in the case of CCS from industrial sources: the so-called "exhaustive" method, the "net present value method", the "annualization calculation method" (Roussanaly, 2019). The "exhaustive" method is shown in Equation 7 while the equations used for calculating the CAC in the other two methods are presented in Appendix G.

$$CAC = \frac{(LCOKM)_{ccs} - (LCOKM)_{ref}}{(t_{CO2}/U_{Km})_{ref} - (t_{CO2}/U_{Km})_{ccs}} \qquad \text{(Eq. 7)}$$

Where, LCOKM is the levelised cost of the key material(s) of the industrial plant with CCS or without in, for example, € per unit of key materials(s) [99], (t_{CO2}/U_{Km}) is the mass amount of CO_2 emitted per unit of key material(s) with or without CCS.

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[11] This means in practice that the emissions associating with building and operating the CO_2 capture facility (CCS chain) are also taken into account.

While the exhaustive method is always valid, it is worth noting that the two other methods do not require the assessment and evaluation of the considered industrial plant hence requiring significantly less effort and data. However, these two approaches also come with limitations and therefore must be used carefully. A summary of assumptions required to ensure the validity of each CO_2 avoidance cost calculation methods is presented in Appendix G.

Note that the CAC is often presented together with a breakdown of cost along the CCS chain, withCO_2 conditioning either lumped together with the capture or transport steps. However, it is recommended here that any cost breakdown of CAC present capture, conditioning, transport, and storage as four individual items.

In power plants, CAC includes the impact of the capture unit on the efficiency of the power plant (as a consequence of using part of the steam and/or generated in the plant to cover the energy needs of the capture unit). In most industrial settings, however, CAC needs to include the costs and CO_2 emissions from additional units e.g., a boiler or a combined heat and power (CHP) system needed to cover the energy requirements of the capture and compression units, or emissions associated to the use of electricity from the electricity grid. Note that not only additional units but also changes in existing units as a consequence of CO_2 capture need to be taken into account. For instance, if the capacity of an existing boiler is increased so it can supply steam to the capture unit, the additional fuel (and related emissions) needs to be allocated to the capture unit and accounted for in the CAC calculation. If, however, waste energy is available at location and no extra units or extra capacities in existing units are required then the costs of CO_2 avoided could be equal to the cost of CO_2 captured (including the cost incurred to utilise the waste heat for CO_2 capture). This only holds if the "waste energy" is really so in practice. Many studies use average amounts of waste energy taken from e.g., literature, and therefore tend to overestimate the amount of waste energy available on-site[12].

CAC is generally used to estimate the minimum CO_2 emission penalty (tax or quota price) that would be required for making a point source without CO_2 capture as expensive as a point source with CO_2 capture (or to estimate the subsidy required to make a point source with CO_2 capture as expensive as a similar point source without it). An important aspect to highlight here is the importance of system boundaries in the calculation of CAC. Strictly speaking, because we are interested in the costs of not emitting one tonne of CO_2 into the atmosphere all emissions should be included, that is direct emissions (i.e. emissions generated in the plant or so-called gate-to-gate emission) and indirect emissions (i.e. emissions taking place outside the industrial plant, for instance during the extraction and transport of fuels, during the production of electricity, the transport and storage of CO_2, or the end life of the product). The wider the system boundaries the lower the avoided emissions and the higher the CAC.

Another indicator that is generally used is *incremental production costs per unit of product*. It relates the costs of capture to the net output of a facility. In a power plant, the impact of capture in the production of electricity is generally assessed through the energy efficiency penalty induced by the capture unit. In an industrial plant, this is less obvious for two reasons. First, it depends on the origin of the energy used to supply the capture requirements e.g., an extra boiler, waste energy, or existing steam. In the latter case (use of existing steam) the capture system may impact the costs and or performance of the unit where the steam was originally used. This impact needs to be assessed and included in the calculation. Second, a key distinction between the power and industrial sector is that most industrial processes do not produce one product and require allocating the incremental costs to the different products. This is discussed in detail in the next section.

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[12] At a given site, however, the energy is for instance not wasted but is actually used to for instance pre-heat a flow, raw material pre-treatment, or for district heat. In such cases, the impact of taking this energy taken away (to be used in the capture unit) should be included in the calculations (for instance by including emissions that will be incurred when replacing the heat source).

2.2.2 The challenge of multi-products in industrial sectors

A key distinction between the power and industrial sector is that many industrial processes produce multiple outputs in a unit. In an atmospheric distillation unit at a refinery for instance, LPG, Naphtha and Diesel/Kerosene are produced. If CO_2 capture would be applied to such a unit, the metric to report the cost of product is not straightforward, as it can be referred to one or more products, including intermediate ones.

This problem is not unique to carbon capture and has been discussed when estimating costs of multi-product industries. A typical approach is to distinguish between *joint costs* (i.e. costs of a production process that yields a number of products where a physical relation exists between the products that prevents one from being obtained independently from the others) and *separable costs* (i.e. cost incurred in processes that produces a single product) [100]. To separate joint costs from separable costs, a split-off point is required as indicated in Figure 2-1. Separable costs are therefore all the costs incurred beyond the split-off point (for instance, cost required for purifying a given product). The costs related to the production of a product (for instance product A) are therefore composed of *part* of the joint costs plus the separable costs of the product. In the simplest joint processes, the joint products are sold at the split-off point (no further processing is required such as for by-product BPc in the figure) and the separable costs are zero.
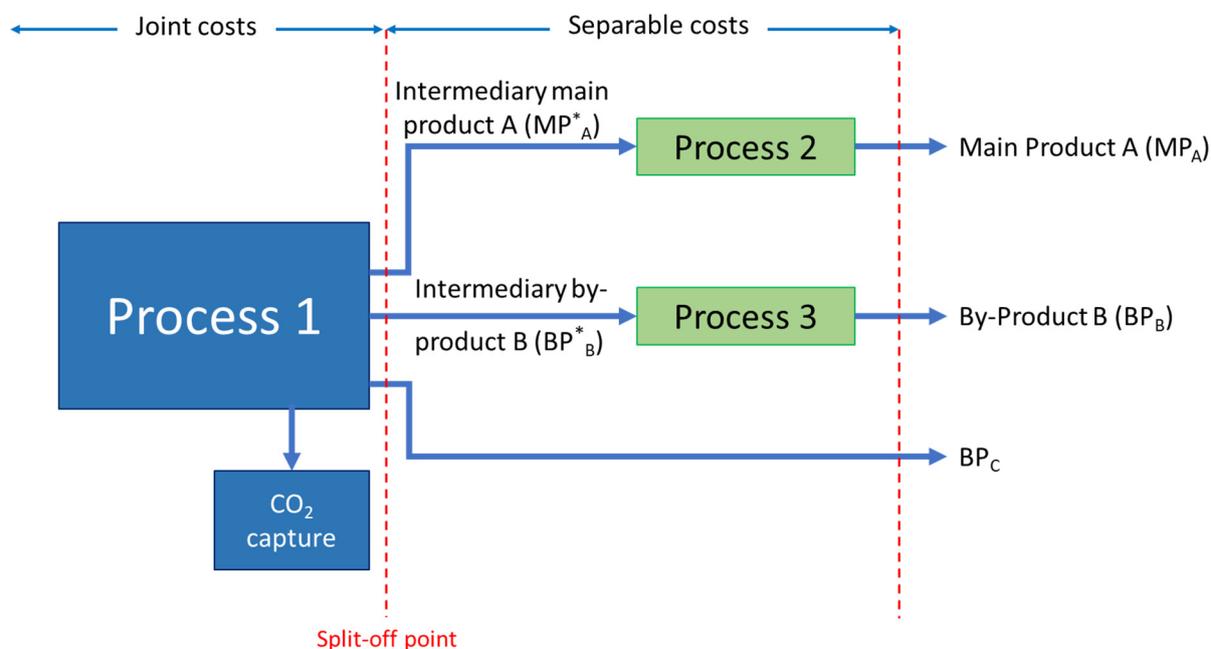
Figure 2-1. Illustration of joint vs separable costs.

There is, however, no standardized methodology currently available to determine the contribution of the different production factors (energy, water, labour) used in the production of each of the joint products at the split-off point. Because in the case of joint costs, one product *cannot* be produced without the other, it is not physically possible to measure the costs of production factors used in the manufacture of each of the joint products. Companies use different methods to allocate the costs to the joint products. In general, all production costs need to be allocated to all products and to do so, companies distinguish between main product(s) and by-products. This distinction is generally made based on the portion of their sales in the total sales of the company. A main product is a product (or products) with significantly higher total sales values compared to the total sales values of other products while by-products are products of a joint process that have low or no total sale value compared with the total sale value of the main product(s). The classification of products (main product or by-product) changes over time and among companies.

The costs allocated to the main products are generally estimated by either:
- o Allocating the costs according to the amount of product produced defined by physical measures such as the share of mass content (the ratio between the total annual production of each product and the total annual refined oil products). This method requires that all the products be measured with the same underlying physical measure (weight, volume, quantity, etc) and is recommended when the different products are homogeneous *and* their sale prices are relatively close to each other.
- o Allocating the costs according to market-based information such as the sale prices of the products. It is based on the assumption that the market price is a proxy for the production costs. In this method, joint costs are, for instance, allocated to the main products proportionally to the sum of the final sales value of the output. Note that if one of the main products cannot be sold as it is (for instance an intermediate product for which there is not known market price and therefore further processing is needed before a main product can be sold in the market), the price incurred to finish the product (separable costs) is subtracted from the sales value of the product. This is called net realizable value and is a hypothetical market value at intermediate stage of production which assumes that all the profit margin is attributable to the joint process and not to the separable costs. Assuming that the capture unit was applied before the split-off point (i.e. part of the joint cost as shown in Figure 2-1), it is worth noting that the larger the separable costs are, the lower is the contribution of the CO_2 capture unit to the total product costs and vice versa.

The costs of by-products can be estimated by:
- o Assigning them no value (costs are therefore only allocated among main products). This method is also known as the Miscellaneous income method. Note that this approach used to be the default approach used to the CO_2 from the capture unit in which no costs were allocated to the CO_2 and all costs were allocated to the main product (e.g., steel or electricity). However, in cases where new options emerge that provide economic value to the CO_2 (CO_2 utilization), an appropriate (case-specific) non-zero value should be assigned. Consequently, even using the same methodology, the estimated costs might vary as these are a function of the final use of the CO_2 and the market for that use. Furthermore, and depending on the CO_2 sales price, there may be cases where the CO_2 may be considered a main product instead of a by-product. In such cases, one must be careful to distinguish between uses of CO_2 that result in permanent (long-term) removal from the atmosphere[13] - as required for GHG mitigation - versus utilization that soon results in the release of CO_2 to the atmosphere and thus does not contribute to GHG mitigation.
- o Assigning them a net realizable value. In this case, the value of selling the product is large enough to have a significant effect in the profits of the company but not large enough to be comparable to the profit of the main product. Note that by allocating costs to the by-product, a reduction in the production costs of the main product(s) will be shown (as the total costs of producing the main products and the by-products is constant).
- o Assigning them a net realizable value minus a given profit value
- o Assigning them the expenditure allocated to the acquisition price or the replacement value on the current market (for instance when a by-product is used within the plant to avoid purchasing materials or utilities, for example, the combustion of a waste to provide heat which avoids purchasing natural gas)

Currently, there are no standardized guidelines of best available practices for selecting allocation methods and, in practice, each company has its own internal approach. To be able to compare capture costs that have been allocated to a given product (including CO_2 that will be used by a third party for CCU) explicit

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[13] It is worth noting that, in such cases, CO_2 utilization could still contribute to reduction of fossil fuel use elsewhere in the overall chemicals manufacturing industrial system. Under specific conditions, this reduction may be considered as contributing to GHG emissions mitigation.

documentation needs to be provided in the number and characteristics (type, amount, concentration, etc) of products and by-products as well as a detailed description of the approach used for allocation. When possible, it is recommended to examine the costs using more than one allocation method as this will provide insights into the impact of the method in the results.

Finally, it is worth noting that similar questions and approaches are considered in life cycle analysis [101]. It is thus important to ensure consistency between techno-economic and life cycle analyses on this point when performing considering cost and emission allocations in multi-products industrial plants [102].

2.3 Considerations for improved assessment of key cost contributors

This section discusses three key contributors to the cost of CCS from industry, which are often not studied in adequate detail are examined and exemplified: 1) energy aspects 2) retrofitting costs 3) CO_2 transport and storage costs.

2.3.1 Energy aspects

CO_2 capture from industrial processes is typically energy-intensive and thus a large part of the CO_2 capture cost is potentially related to the use of energy. For example, the steam consumption for MEA solvent regeneration in a cement plant typically contributes to nearly 50% of the CO_2 capture cost[14] [80]. Heat (mainly in the form of steam) and electricity are the two main forms of energy needed by CO_2 capture processes. The form of input energy differs per capture technology and facility; for example, oxyfuel and membrane-based systems use electricity while chemical absorption systems require both heat and power. In practice, several key factors determine the cost and CO_2 emissions associated with energy consumption: type of energy used (electricity and heat), origin and supply strategy of energy, costs and emissions intensity of the primary energy source, and possibility to export excess energy to third parties. Most of these factors are region- and facility-specific and may not only affect the CO_2 avoidance cost but also the comparison of CO_2 capture technologies. Therefore, in studies related to CO_2 capture in industrial processes, it is recommended to discuss the sensitivity of the CO_2 avoidance costs with respect to the choice of facility characteristics, fuel prices, energy supply, and export alternatives. The effect of the choice of energy supply alternatives is discussed below with an example on CO_2 capture in a cement plant.

2.3.1.1 Energy supply strategies

The origin and production/supply strategy of steam and electricity have a significant impact on their production costs and associated CO_2 emissions, and may thus significantly impact the CO_2 avoidance cost. While a given heat and power supply strategy is often implicitly adopted in the evaluation of CO_2 capture technologies, it is important to realise that this implicit assumption may impact significantly the CO_2 avoidance cost of a capture technology as well as the comparison of capture technologies.

Figure 2-2 illustrates different steam and electricity supply strategies in the case of a cement plant integrated with an MEA-based absorption CO_2 capture unit [80], while Table 2-2 presents their associated costs and CO_2 emissions intensities. As seen in Table 2-2, extracting steam from a low-pressure turbine or steam originating from waste heat recovery in core industrial processes are cheaper options and have lower CO_2 emissions intensity. Thus, integrating excess heat available in the industrial plant or in another facility near the CO_2 capture unit is expected to be a cost-effective solution. However, it should be noted that a large amount of good quality waste heat is rarely available in industrial plants and should be expected to be further driven down by energy efficiency improvement efforts. On the other hand, an electric boiler can in general appear as an inefficient way of producing steam for the CO_2 capture unit. However, it is important to also realise that the cost and associated emission intensity of a steam strategy depends on the site-specific characteristics, as well as external parameters such as energy prices.

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[14] When a natural gas boiler is used to produce steam and the waste heat from the original facility available to invest on the CO_2 capture system is limited.
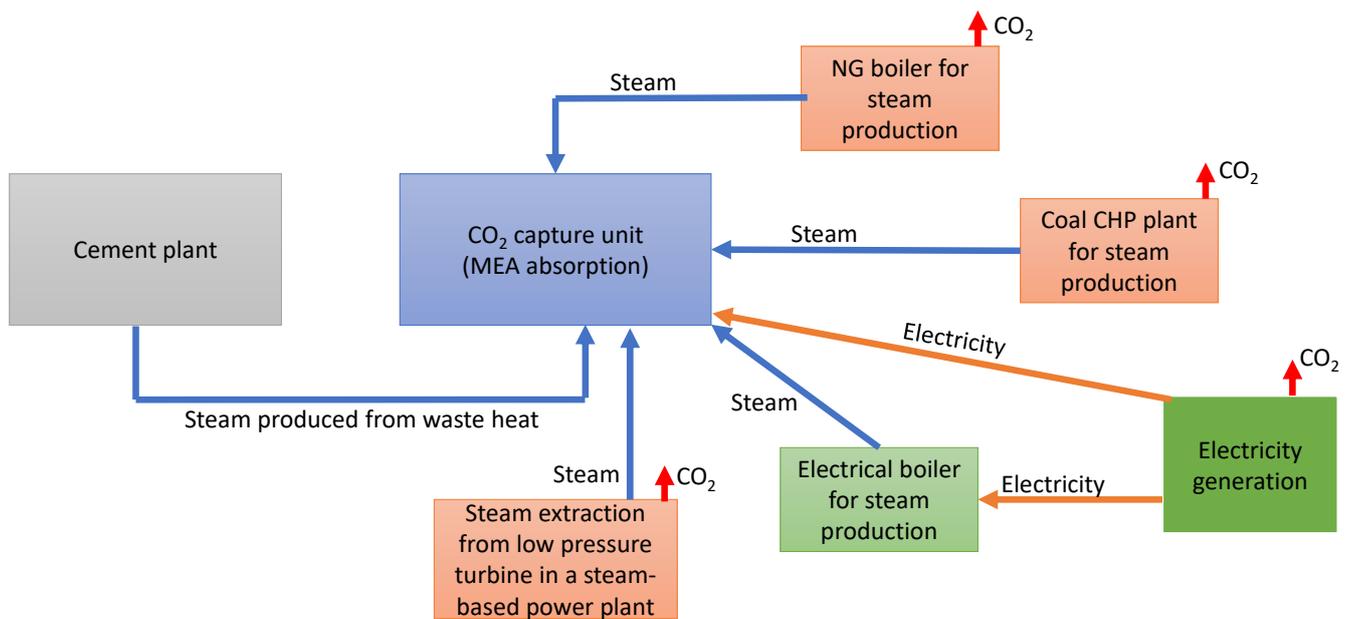
Figure 2-2. Schematic illustrating different means of producing and supplying energy for an MEA-based CO_2 capture in a typical cement industry.

Table 2-2: Cost and CO_2 emission intensity of different stream supply options

Source	Emission intensity [kgCO$_2$/GJ]	Steam cost [€$_{2015}$/GJ]
Electric boiler	87	18
Natural gas boiler	57	7.2
Natural gas-CHP plant	57	6.4
Coal CHP plant	127	6.1
Steam extraction from an LP Turbine	49	3.7
Excess heat from industrial core process	0	1.9

Table footnote: These costs are based on the heat supply evaluation performed in the CEMCAP project. [80, 90]. These were established for a generic Netherlands-based application, in the context of CO_2 capture from a cement plant, with an NG price of 6 €/GJ, a coal price of 3 €/GJ and an electricity price of 58 €/MWh, and a CO_2-intensity associated with electricity consumption of 306 gCO$_2$/MWh. A project duration of 25 years and a real discount rate of 8% are considered.

2.3.1.2   Impact of energy prices

The cost of the energy supply is directly linked with the price of input energy sources (fuel or electricity). However, the energy source prices can vary significantly based on local market conditions, local environmental policy framework, and their possible future evolutions [103]. It is thus important to also understand the impact of these energy source prices on the steam production cost.

Figure 2-3(a, b, c) shows an example of a sensitivity analysis of the steam cost as a function of the price of coal, natural gas, and electricity respectively. As can be seen from these, the energy prices can significantly impact the selection of an optimal steam production strategy. Overall, steam extracted prior to an LP turbine or generated based on available waste heat remain the cheapest options in most situations. However, if electricity prices are high, gas- or coal-CHP can be very attractive options as these would also result in the production of high-value electricity.

Finally, it is important to realise that some of these energy prices are linked. For example, higher global coal and gas prices can be expected to lead to higher global electricity prices. As a result, a heat and power production unit used for CO_2 capture and also selling excess electricity might be less impacted by an increase in fuel prices due to high electricity revenues. Similarly, carbon prices/taxes increase overtime to penalise CO_2 emissions can also significantly impact the performance and selection of heat and power

supply strategies. A possible way to deal with these uncertainties is to make scenarios about future plausible combinations of energy and carbon prices to clearly understand the variety of possible outcomes.

(a) Impact of coal price

(b) Impact of natural gas price

(c) Impact of electricity price
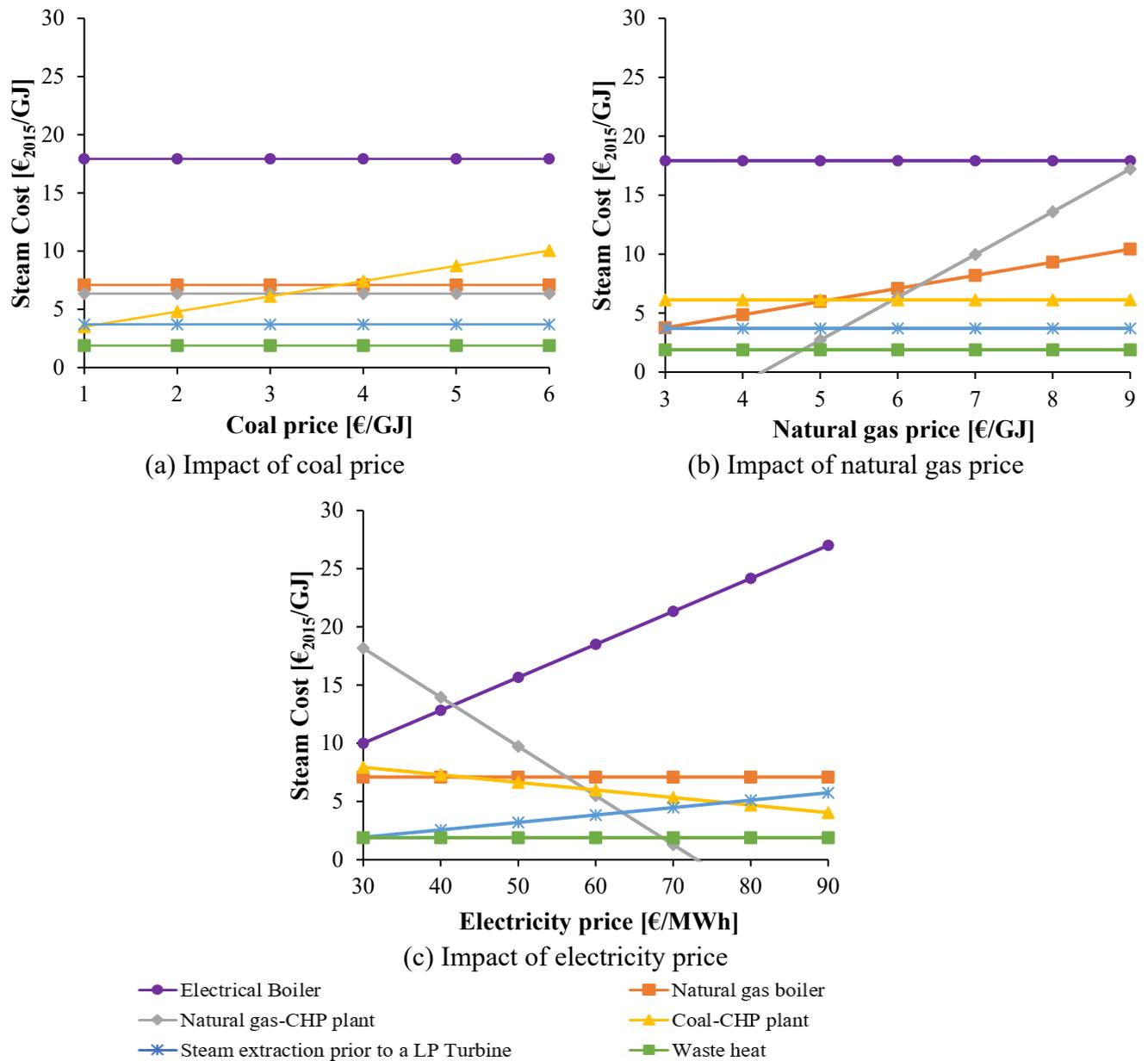
Figure 2-3. Impact of energy prices on the steam cost for different steam supply strategies: a) coal price b) natural gas price c) electricity price

Figure footnote: Results included in these figures were calculated on the same basis as Table 2-2, while the energy (coal, natural gas, electricity) prices are here varied to understand their impact on the steam cost.

2.3.1.3 Credits for import and export of energy

In some cases, energy is imported or exported from the industrial site due to the implementation of CO_2 capture, resulting in a change in energy production and consumption, and related CO_2 emissions produced elsewhere in the energy system (indirect emissions). Similarly, the economics of the capture case may be impacted due to the purchase or sale of energy from or to third parties.

One way to account for these effects is to assign credits or penalties to the costs and CO_2 emission reductions in the CO_2 capture case. Cost and environmental penalties or benefits from the energy import or export will be site- and region-specific, and will also depend on the reference case without CO_2 capture [88]. For example, the potential electricity exported to the grid will displace electricity generation

elsewhere in the broader energy system; this can for example be electricity generated in a coal-fired power plant or renewable electricity, each with a different carbon-intensity. Credits for emission savings elsewhere in the broader energy system will depend on the CO_2 emissions factor of the electricity grid, and can therefore vary significantly from one region to another.

The credits can be calculated by multiplying the imported or exported energy with an energy price and CO_2 emission factor based on life cycle analysis, which best reflect the reference case. In many cases, this is a fair approach, especially when it concerns the export of excess fuel and steam coming from the core industrial process, which may have changed due to the CO_2 capture process. However, this approach is arguably less fair when considering the export of steam or electricity from newly built energy plants. After all, the generation and export of large amounts of electricity and steam could create economic revenues and emissions savings (if it displaces more carbon-intensive energy elsewhere in the broader energy system), and not allocating these credits to the CO_2 capture case could distort its techno-economic performance [104]. An alternative accounting method is to exclude revenues from excess electricity and steam generation as well as the costs for the share of the fossil fuel or biomass of the energy plant that corresponds with this excess energy production (which can be determined on an exergy, energy, or economical basis). While there is not an inherently best accounting method, this can have a large impact on the computed avoidance costs and emissions of the capture case. Study practitioners should thus be explicit on their considered accounting method.

2.3.1.4 Effect of energy aspects on CO_2 avoidance costs and choice of capture technology

To illustrate the effect of energy supply strategy on the CO_2 avoidance costs and comparison of two capture technologies (MEA-based absorption and membrane-assisted liquefaction) in a cement plant [80], an example of 7 scenarios are presented in Figure 2-4 in order to highlight the energy aspects discussed above. In particular, these scenarios combine different steam supply strategies (natural gas boiler, extraction prior to a low-pressure steam turbine, electricity boiler), electricity prices (30 and 80 €/MWh), and natural gas prices (6 to 9 €/GJ). While none of these scenarios consider CO_2 capture from ancillary energy supply unit(s), it is worth noting that this together with switching to bio-based energy are key to reach deep emissions reductions across the industrial process [105]. However, CO_2 emitted from these ancillary units should be captured and geologically stored as well to achieve deep levels of decarbonisation, and these costs should be represented in the overall CO_2 avoidance cost.

As can be seen in Figure 2-4 the selected steam supply strategy can have a significant impact on the technology comparison. In the heat supply scenarios, MEA-based is the most cost-efficient capture technology in the natural gas boiler and steam extraction prior to a LP turbine scenario (respectively scenarios 1 -also referred as base case- and 2). On the other hand, the membrane-assisted liquefaction is the most cost-efficient capture technology if steam must be supplied through an electric boiler (scenario 3). It is also worth noting that the CO_2 avoidance cost of the cost-optimal capture technology may or may not be impacted. For example, compared to the natural gas boiler scenario, the steam extraction scenario results in significantly lower CO_2 avoidance cost for the optimal capture technologies, while the electric boiler scenario result only in slightly lower costs.

Figure 2-4 also illustrates that energy prices can also have an impact on the CO_2 avoidance cost, as well as on the comparison of technologies. Compared to the base case, a higher natural gas price favours the membrane-assisted liquefaction (scenario 4) while a higher electricity price would favour the MEA-based capture (scenario 5). The potential impact of CO_2 emissions associated with heat and electricity consumption can also be visualised by comparing the scenarios 3 and 6 (both based on heat supply through an electric boiler). As electricity is assumed to be based on renewable source in this scenario, no CO_2 emissions are associated with the consumption of heat and electricity thus resulting in lower CO_2 avoidance cost. Finally, scenario 7 combines a reduction in electricity prices and no CO_2 emissions associated with power. In this case, steam produced from an electric boiler results in lower CO_2 avoidance cost than the base case (scenario 1) as well as nearly on par CO_2 avoidance costs between the two CO_2

capture technologies. Although scenario 7 may seem far-fetched for most locations, it is representative of conditions for CO_2 capture in Norwegian industrial plants[15].

Building on the energy aspects discussed previously, these scenarios further emphasize the importance for TEA practitioners to consider the impact of possible energy supply strategies as well as possible evolution of global energy scenarios.

Steam supply strategy	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7
	NG boiler	LP steam extraction	Electric boiler - EU	NG boiler	NG boiler	Electrical boiler - CE	Electrical boiler - CE
Natural gas price [€/GJ]	6	6	6	9	6	6	6
Electricity price [€/MWh]	58	58	58	58	80	58	30
Electricity CO_2 emissions [kgCO_2/MWh]	306	306	306	306	306	0	0
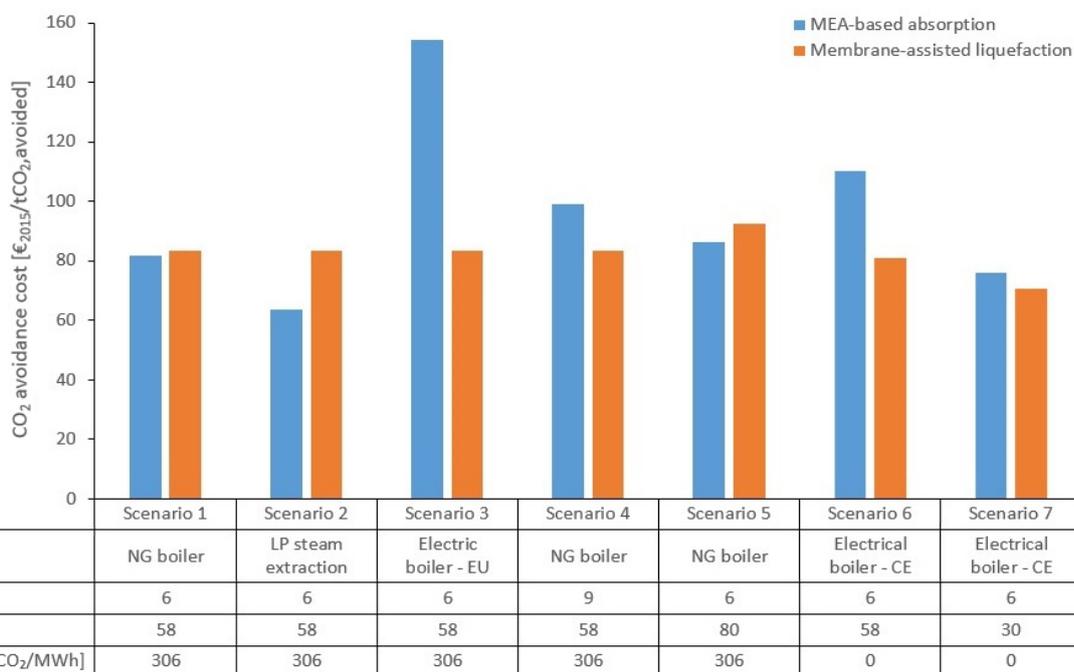
Figure 2-4. Illustration of the impact of different energy scenarios on the CO_2 avoidance costs and the comparison of two capture technologies (MEA-based absorption and Membrane-assisted liquefaction)

Figure footnote: The performance of the MEA-based and membrane assisted liquefaction for CO_2 capture from a cement plant are extracted from the CEMCAP project [80]. These were established for a generic Netherlands-based application, a project duration of 25 years, and a real discount rate of 8% .

"NG boiler" corresponds to natural gas boiler; "LP steam extraction" corresponds to steam extraction prior to a low-pressure turbine; "Electric boiler – EU" corresponds to electric boiler powered by electricity with the characteristics of the average European Union electricity mix; "Electric boiler – CE" corresponds to electric boiler powered by the clean electricity thus it is assumed to not result in any CO_2 emissions.

2.3.2 Retrofitting costs

In retrofitting an industrial plant with a CO_2 capture process, several plant-specific and technology-specific characteristics can entail significant costs and considerations for the CO_2 capture process that are often overlooked in techno-economic studies of industrial CCS applications. This section aims to highlight some of the most important retrofitting cost aspects and provides several numerical examples for illustrating these.

2.3.2.1 Economic impact of plant production stop for CO_2 capture retrofit

Retrofitting of CO_2 capture technologies at an industrial plant might involve a temporarily shut down, fully or partially, especially if fundamental modifications to the core process are required. The resulting production losses can have non-negligible economic consequences, depending on the type of process, integration of the CO_2 capture system with the original facility, and economies of scale, and will therefore have to be kept to an absolute minimum. For certain industrial applications and CO_2 capture technologies, e.g. oxyfuel or pre-combustion technologies in cement or iron and steel applications, a significant downtime might be required to modify the existing industrial plant for deep integration with the CO_2

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[15] Although the CO_2 footprint would not be zero if assessed through a full life cycle analysis.

capture plant. For other end-of-pipe technologies that do not require significant integration with the core process, other than re-routing of the flue gas, it could be expected that the retrofit period is aligned as much as possible with a routinely scheduled production stop for maintenance to minimize the economic impact. In some cases, it might be possible to only shut down parts of the core plant for the retrofit and thereby avoiding 100% production losses, e.g. in a plant with several emission sources where only a single source is retrofitted with CO_2 capture or a plant with multiple production lines. This could be the case in a modern steel mill or a multi-product oil refinery where the production process is not necessarily linear. Although not exemplified here, it should be mentioned that the same considerations for plant production stop and economic consequences also apply in retrofitting CO_2 capture to power plants. In any case, costs arising from plant production stop should transparently be taken into account in estimating the costs of CO_2 capture.

The economic impact of production stops for retrofit is exemplified below for three different industrial plants: a cement plant [80, 106], a pulp mill [82], and an integrated steel mill [78]. Key data for these industrial plants is listed in Table 2-3.

The added cost of CO_2 avoided due to a production stop for CO_2 capture retrofit for the three industrial plants are exemplified in Figure 2-5, for production stop in the range of 500-4000 hours and under specific assumptions on the loss of profit. During the production stop, fixed running costs and annualized capital costs[16] are accounted for together with the loss in profit (for example with a 20% profit margin on the product cost). From it is evident that a lengthy production stop for retrofitting CCS has a significant economic impact and will add considerably to CO_2 avoidance costs, especially if only a small part of the production stop can be aligned with a routinely scheduled production stop for maintenance. This can be exemplified in retrofitting a cement plant with oxyfuel technology, where, under specific assumptions, a 4000-hours production stop for significant modifications to be implemented in the core process would increase the CO_2 avoidance cost by over 15%, assuming a 20% profit margin on the product. In the case of retrofitting a pulp mill's recovery boiler with amine CO_2 capture, a shorter production stop of 1000 hours might suffice for the end-of-pipe technology, resulting in around 6% increase in the CO_2 avoidance cost.

In addition to the length of the production stop, the product profit margin will also impact the added cost of CO_2 avoided, as exemplified in Figure 2-5, for a production stop of 500, 1000, and 4000 h in a cement plant, pulp mill, and an integrated steel mill.

Table 2-3: Examples of key data for three different industrial plants.

Plant type – product	Cement plant (CEMCAP [80]) – clinker	Pulp mill (IEAGHG [82]) – air-dried pulp	Integrated steel mill (IEAGHG [78]) – hot rolled coil
Production rate [tonne of product/hour]	120	95	500
Production cost without CCS	63 $€_{2014}/t_{clinker}$	523 $€_{2015}/adt^a$	451 $€_{2014}/t_{HRC}^{a,b}$
CAPEX and fixed OPEX of plant	39 $€_{2014}/t_{clinker}$	248 $€_{2015}/adt^a$	204 $€_{2014}/t_{HRC}^{a,b}$
CO_2 emissions in normal operation w/o CO_2 capture [tCO_2/h]	103	257	1047

[a] adt and hrc stand for air-dried ton and hot-rolled coil, respectively.

[b] Costs converted from $2010 to €2014 using the Chemical Engineering Cost Plant Index (CEPCI) and average currency exchange rates.

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[16] Repayment of investment and operating costs such as labour, maintenance, etc.
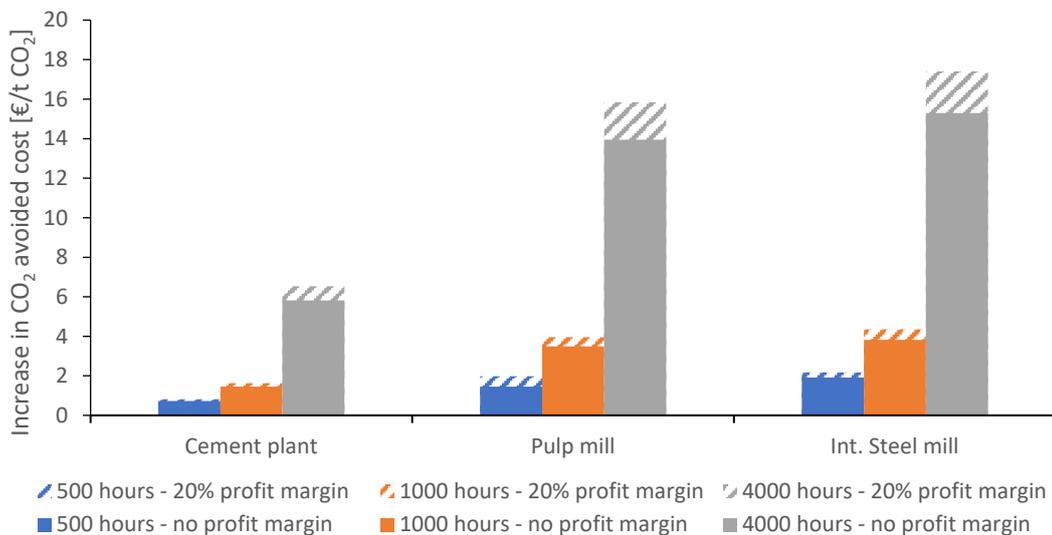
Figure 2-5. Increase in CO₂ avoided cost, as a result of a whole-plant production stop, for production stop durations from 500 to 4000 hours, and with profit margin losses on the product cost during production stop of 0 and 20%.

Figure footnote: During the production stop, fixed running costs and annualized capital costs are accounted for together with the loss in profit. The increase in CO_2 avoided cost is calculated by dividing these costs and profit loss during the plant stoppage over the discounted amount of CO_2 avoided over the expected numbers of operation of the CO_2 capture facility. Here, 25 years of operation and a real discount rate of 8% are considered. It should be noted that for simplification, the amount of CO_2 avoided is calculated with a 90% CO_2 capture rate, 90% capacity factor of the industrial plant, and does not account for emissions originating from potential increase in energy demand of the industrial plant after CO_2 capture is implemented.

2.3.2.2 Impacts on the product quality and plant operation

The integration of CO_2 capture technologies can also have an impact on the main output product(s) of the plant. For example, if no other process modifications are implemented, CO_2 oxyfuel combustion in a cement plant has a direct impact on the temperature in the cement kiln, which can negatively affect the clinker phase formation and consequently the product quality [107]. Another example is oxyfuel combustion in the blast furnace of an integrated steel mill. In this case, H_2 and CO rich flue gases from the furnace are partly recycled, after the CO_2 has been separated from the gases, to regulate the mass and energy balance of the furnace. This drastically different atmosphere in the furnace can affect the product to some extent but will also have a large impact on the energy balance of the whole steel mill which could make this technology difficult to implement in existing plants [108].

Implementation of capture technologies that affect the core plant´s main product may result in additional costs for modifications of the original process and equipment, post-treatment to meet existing product standards, or a decrease in product value. In such cases, both should be attributed to the cost of CO_2 capture. A lower product value will most likely yield lower revenues. These situations are more likely to occur in retrofit applications, where changes to the primary process may be less feasible than in new plant applications. Conceivably, however, technology innovations and process modifications to accommodate the new carbon constraint may also result in net benefits and cost savings (as occurred, for example, when CFCs were banned from certain industrial processes).

In practice, it can be challenging to assess foregone revenues (or additional profits) since the exact market value (product price) is often unknown. If a sound assessment is not possible, practitioners of costing studies should at least clearly report the assumed cost effect and consider sensitivity analyses. In general, the required product quality is dictated by consumers' demands. For that reason, maintaining the product quality will often have priority for the plant operator.

2.3.2.3 Spatial constraints for CO_2 capture equipment in existing industrial plants

Space restrictions or safety considerations on industrial sites could severely affect the technical and economic feasibility of installing CO_2 capture equipment and their supporting utilities on industrial sites. Unlike new-build (greenfield) plants with CCS, existing (brownfield) facilities were not designed to accommodate spacious capture equipment, thus possibly making retrofit applications of CCS more challenging and costly. Although spatial constraints vary considerably on a case-by-case basis, depending on the design and layout of the plant as well as on the capture technology, infrastructural modifications (e.g. flue gas re-routing and sub-optimal unit location) and replacement of existing installations on the plant site, may be required [93, 109].

In most cases, spatial constraints can be solved by placing the CO_2 capture unit, or part of it, further away from the emission point source. However, this implies flue gas transport over longer distances, requiring large-diameter and expensive stainless-steel ducting, and possibly modifications to the existing industrial plant. In addition, the transport of the gaseous flue gas through the ducting system might be very energy-intensive and thus costly and may even require additional equipment (e.g. blowers). In some cases, alternative capture configurations in which only part of the capture unit is placed near the emission point source can provide a workable solution. For example, in some cases, it could be more cost-efficient to locate only the absorption section of an amine-based capture process near the CO_2 emission point and transport the CO_2 absorbed in the rich solvent to the regeneration and CO_2 compression section located further away [93, 110]. In addition, capture configurations can even span multiple industrial plants whereby capture components, such as solvent regenerators and compressors, may be shared. Such configurations do not only circumvent spatial limitations on individual plant sites, but may also offer the possibility to curtail average capture costs by exploiting economies of scale compared to a set of individual plant chains [111].

Figure 2-6 illustrates six stylised examples of layout alternatives that may be considered depending on potential spatial constraints for a solvent-based CO_2 capture process. Case (a) represents the scenario in which there is enough space near the flue gas point source to accommodate the absorber, desorber, and compression sections of the capture process. This case tends to be more cost-effective when considering CO_2 capture from a single CO_2 point source as it minimises the high cost associated with the flue gas ducting and rich/lean solvent transport. Case (f) represents the other extreme in which both the absorber and desorber sections are placed far away from the flue gas point source due to spatial constraints. This option tends to result in significantly higher cost than case (a) due to the large flue gas ducting required. Meanwhile, cases (b) to (d) represent hybrid configurations. For example, in case (b), there is enough space near the flue gas point source for the absorption section but not for the desorber section. As a result of this, the desorber may be placed further away from the flue gas point source and the CO_2 would be transported as a CO_2-rich solvent between the two sections of the CO_2 capture process. Case (c) is similar to case (b) with the exception that it considers that the spatial constraint would lead to flue gas ducting to reach an area with sufficient space for the absorber section. Finally, cases (d) and (e) illustrate that further complexity may arise when considering CO_2 capture from multiple sources, with potentially different CO_2 concentrations and impurities, within the plant which may be the case for example for refineries, iron and steel mills, etc.

Flue gas point source

Absorber section

CO$_2$ regeneration and
compression section

CO$_2$ to fence

(a)　(b)　(c)　(d)　(e)　(f)
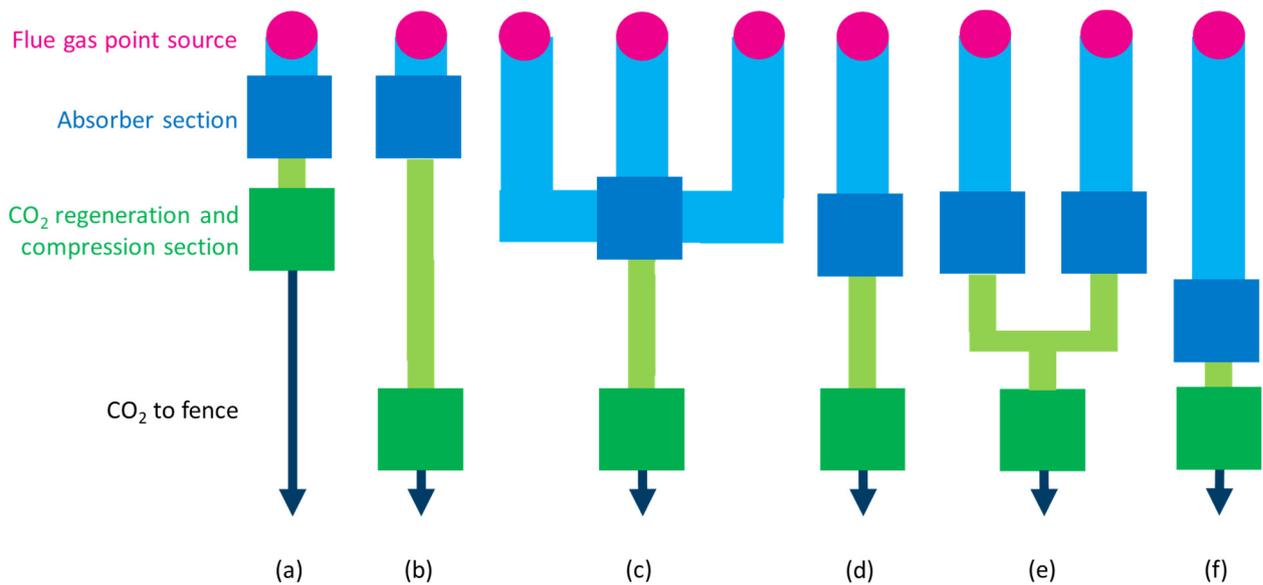
Figure 2-6. Illustration of different layout alternatives that could be considered in space-constraint cases.

In general, the additional costs resulting from spatial constraints are not always considered, outside of detailed engineering studies, when discussing costs of CCS in industry. Although this can be a reasonable assumption when considering greenfield development of the industrial plant with CCS [112, 113], in other cases this may not be justified as these costs may increase the cost of CO$_2$ capture and conditioning in a non-negligible way. For example, in the case of CO$_2$ capture retrofit to a refinery, the flue gas and utilities interconnection costs were estimated to be in the range of 16-35 €$_{2015}$/tCO$_{2,avoided}$ for different unit retrofit scenarios [93]. Furthermore, as space requirements for the CO$_2$ capture unit is technology-specific, spatial constraints may significantly benefit compact and modular capture technologies, as they could avoid significant flue gas interconnection costs [106], thus impacting the capture technology selection.

Although the impact of spatial constraints and flue gas interconnection costs ought to be considered in techno-economic studies on CO$_2$ capture retrofit from industrial plants, it is important to realise that these costs are very much site and CO$_2$ capture technology-specific. These costs shall thus be based on the evaluation of the layout of the industrial site with the considered CO$_2$ capture technology. In order to better help accounting for these costs, an example of the direct costs associated with the installation of a pipeline rack with a flue gas duct are illustrated in Figure 2-7 as a function of the exhaust flue gas flowrate for different transport distances (d).

Finally, the costs associated with utilities[17] production and their integration with the CO$_2$ capture unit can also be impacted by space constraints. In some cases, the CO$_2$ capture unit may be located at significant distances from relevant utilities production and treatment facilities. This may happen in cases in which new utilities production and treatment facilities could not be placed close to the CO$_2$ capture unit due to space constraints. However, this may also be the case when existing utilities production and treatment facilities with spare capacity are integrated with the CO$_2$ capture unit in order to reduce costs and/or investment. Although these are rarely included in cost evaluations, these costs can be non-negligible in retrofit cases depending on the overall layout of the industrial plant with the CO$_2$ capture unit and its associated utilities. Thus, these costs must be included to make more realistic cost estimates as well as to better understand the complete impact of certain design decisions such as the use of existing spare capacities.

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[17] Power, heat, cooling water, process water, etc.
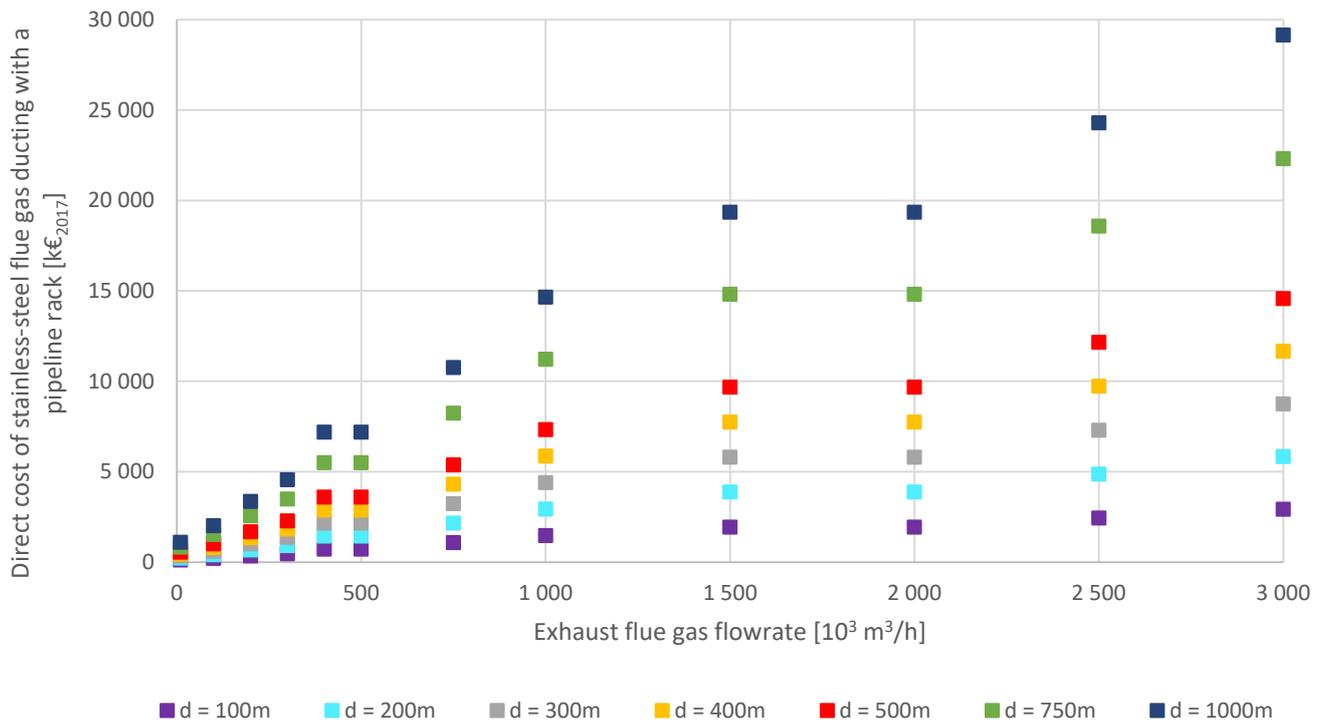
Figure 2-7. Direct cost associated with exhaust flue gas ducting in function of the exhaust flue gas flowrate for different transport distances (d)

Figure footnote: These costs, estimated with Aspen Process Economic Analyzer [114], correspond to direct costs associated with the installation of a pipeline rack with a flue gas duct in stainless steel 304[18] for a Dutch-based location.

2.3.2.4 Flue-gas treatment requirements

Another element which can have a significant impact on the costs of CO_2 capture from industrial plant is the presence of impurities in the flue gas to be treated in the CO_2 capture process. Indeed, industrial flue gases can contain levels of impurities which may impact the performances and design of the CO_2 capture and downstream CCS system. For example, the presence of SO_X and NO_X can lead to significant solvent degradation in an amine-based CO_2 capture thus resulting in poorer capture levels, higher energy penalties, and a more costly process. Similarly, certain membranes can be very sensitive to the presence of water while others are not. Depending on type and level of impurities of the plant flue gas and the technologies considered along the CCS chain, pre-treatment might thus be required prior or downstream of the CO_2 capture process to reach satisfactory levels of impurities. This could for example mean desulphurisation (DeSO$_X$), NO_X removal, oxygen removal, dehydration, dust removal, etc. The cost associated with this or these potential treatment(s) may have a significant impact on capture costs, the comparison of capture technologies [115], as well on the performances and technology selection in the transport and storage part of the chain [116, 117]. Cost studies that ignore these additional costs or fail to attribute them to the cost of CCS might understate the real costs of CCS.

Typical ranges of flue gas CO_2 content and levels of SO_X, NO_X, and dust in different industry flue gases are summarised in Table 2-4.

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[18] Stainless steel 304 is here considered due to the expected presence of water in the flue gas. It is worth noting that the material selection may differ depending on water level, as well type and level of other corrosive impurities.

Table 2-4: Typical CO_2 concentrations and impurities in flue gas prior to CO_2 capture in various energy-intensive industries. Note that other impurities than listed here might be present as well.

Industry	CO_2 source within facility	CO_2 concentration (%vol)	SOx	NOx	Particulate matter
Cement [79, 106, 115]	Cement kiln stack	18-22	10- 3500 mg/Nm^3	200-3000 mg/Nm^3	5-200 mg/Nm^3
Iron and steel [78, 108, 118]	Power station Blast furnace Other stacks	25-30 25 14-25	10-20 mg/Nm^3 10 mg/Nm^3 10-300 mg/Nm^3	50-60 mg/Nm^3 60 mg/Nm^3 30-500 mg/Nm^3	<5 mg/Nm^3 <5 mg/Nm^3 <5 mg/Nm^3
Oil refining [86, 93, 119]	Fluid Catalytic Cracker Process heaters stacks*	14-17 8-14	700-800 mg/Nm^3 5-350 mg/Nm^3	- 80-350 mg/Nm^3	- -
H_2 production [86, 93]	Steam methane reformer	20-25	60 mg/Nm^3	120-150 mg/Nm^3	-
Pulp and paper [82]	Recovery boiler	13	1-100 mg/Nm^3	120-250 mg/Nm^3	5-190 mg/Nm^3

* Flue gases from different process heaters vented through the same stack

To illustrate the impact additional flue gas treatment can have on capture cost, additional costs for DeSOx pre-treatment are exemplified in Figure 2-8, for different cement and oil refinery flue gases [80, 93, 106]. The presence of DeSOx treatment in industrial plants is indeed highly industry- and site-specific and depends on the nature of the core production process, the characteristics of fuels used in the process as well as local environmental legislations. Industrial plants might fulfil SOx emission standards without a DeSOx system, but when it comes to implementing CO_2 capture, some post-combustion systems might require reduction of SOx to lower levels to minimize detrimental effects on the capture process performance. In that sense, there is an economic trade-off between the extent of additional flue gas purification and less deteriorating effects on capture process performance.

Considering treatment requirements downstream of the CO_2 capture unit, the high purity CO_2 stream from the CO_2 capture system needs to reach the quality requirements of the transportation system or the CO_2 utilisation process. Similarly, the cost linked to that post-treatment needs to be considered in the whole CCUS system evaluation.
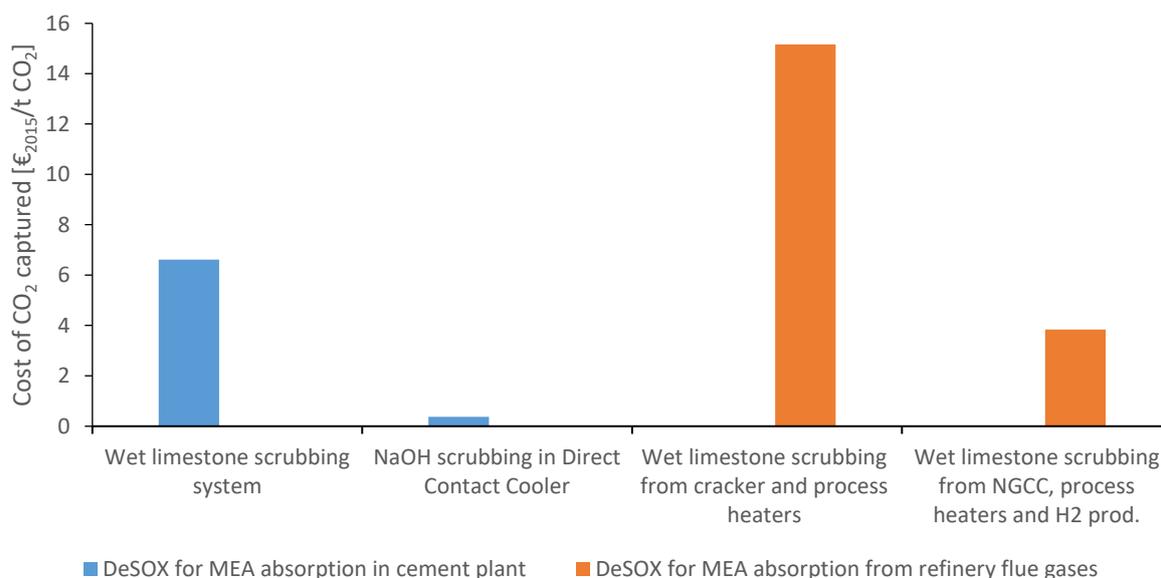

Figure 2-8. Cost of flue gas desulphurisation [€$_{2015}$/t CO_2 captured], exemplified for MEA absorption applied on cement plant and refinery flue gases.

Figure footnote: Based on data extracted from the studies on CO_2 capture from a cement production facility [80] two flue gases from a refinery [93].

2.3.3 CO_2 transport and storage costs

Several studies have discussed the costs of CO_2 transport and storage in detail [120-122]. In practice, it is important to note that these costs are influenced by a variety of factors: transport mode (e.g. pipeline, ship), flow rate, transport distance, spatial configuration of transport system, type of storage (e.g. saline aquifer, depleted gas field), and characteristics of storage site (e.g. storage capacity, permeability, porosity).

This section discusses key cost aspects related to transport and storage of CO_2 captured from industrial point sources. It is worth noting that estimates presented in the section exclude the CO_2 conditioning (purification and compression) costs at the capture facilities unless otherwise indicated.

2.3.3.1 Impact of the amount of CO_2 captured on transport and storage cost

Industrial plants vary considerably in terms of annual CO_2 emissions, typically ranging from 0.15 $MtCO_2/y$ to 14 $MtCO_2/y$ depending on size and type of the individual plant (see Table 2-1). Consequently, the amount of CO_2 captured, and thus transported and stored, can vary significantly. In addition, plant operators may decide to capture only a share of the plant's CO_2 emissions, either because it is physically impossible to capture all CO_2 emissions due to spatial constraints (see Section 2.3.2.3), or because of economic reasons. Many industrial plants have multiple point sources with different characteristics in terms of waste heat availability, spatial constraints, and CO_2 volume and concentration, resulting in varying CO_2 capture costs. As a result, plant operators may only capture CO_2 from the point sources with the lowest cost, depending on the policy framework [93, 123].

The cost of CO_2 transport and storage is strongly linked to the CO_2 flow rate, which in turn is a function of the CO_2 capture rate at the industrial plant. As a result, transport and storage costs may differ significantly from one industrial plant to another and make up a considerably larger share in the total CCUS chain cost for smaller emitters. Nevertheless, many literature studies assume a fixed cost for CO_2 transport and storage (often 10 €/tCO_2) regardless of their considered CO_2 flow rate [21].

Figure 2-9 to Figure 2-11 illustrate costs of transport and storage per tonne of CO_2 for the Northwest European region. These estimates illustrate how costs of CO_2 transport and storages can sharply decrease with higher CO_2 flow rates due to economies of scale, and hence why an assumed fixed CO_2 transport and storage cost independent of the considered flow, distance to storage and storage characteristics may not be appropriate. While the estimates presented in Figure 2-9 to Figure 2-11 could already support better CCS estimates more representative transport and storage costs, case-specific evaluations also reflecting cost specific to the considered region are recommended.

It is also important to note that pooling demand for transport and storage capacity by sharing pipeline and storage infrastructures can significantly reduce the average unitary cost, which might be particularly beneficial for small emitters. For example, for a transport distance of 250 km via onshore pipeline, increasing the annual transport flow rate from 0.5 to 5 $MtCO_2/y$ would reduce average transport cost more than three times, from over 20 €$_{2017}$/tCO_2 to around 6 €$_{2017}$/tCO_2 (see Figure 2-9). While a shared infrastructure may have lower total system costs than a set of stand-alone solutions, it does involve several challenges, including higher upfront investments as well as coordination and cost allocation among the different users.
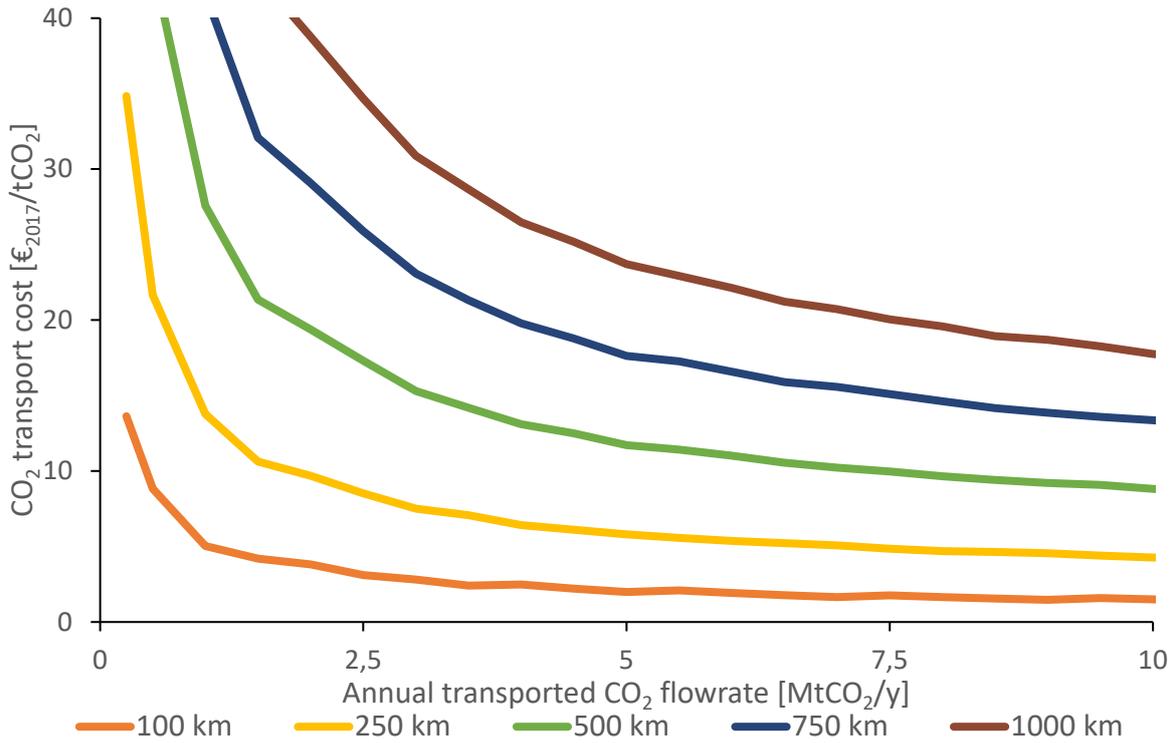
Figure 2-9. CO_2 transport cost via onshore pipeline in function of the annual transported CO_2 flowrate for different transport distances

Figure footnote: Established using the iCCS tool [124, 125] and considering the pipeline cost model from Knoope et al. [126]. While the CO_2 is assumed to be available at 110 bar after CO_2 conditioning, the pipeline diameter and number of reboosting station(s) is optimised for each combination of transport flowrate and distance. These estimates are based on a project duration of 25 years and a real discount rate of 8%.
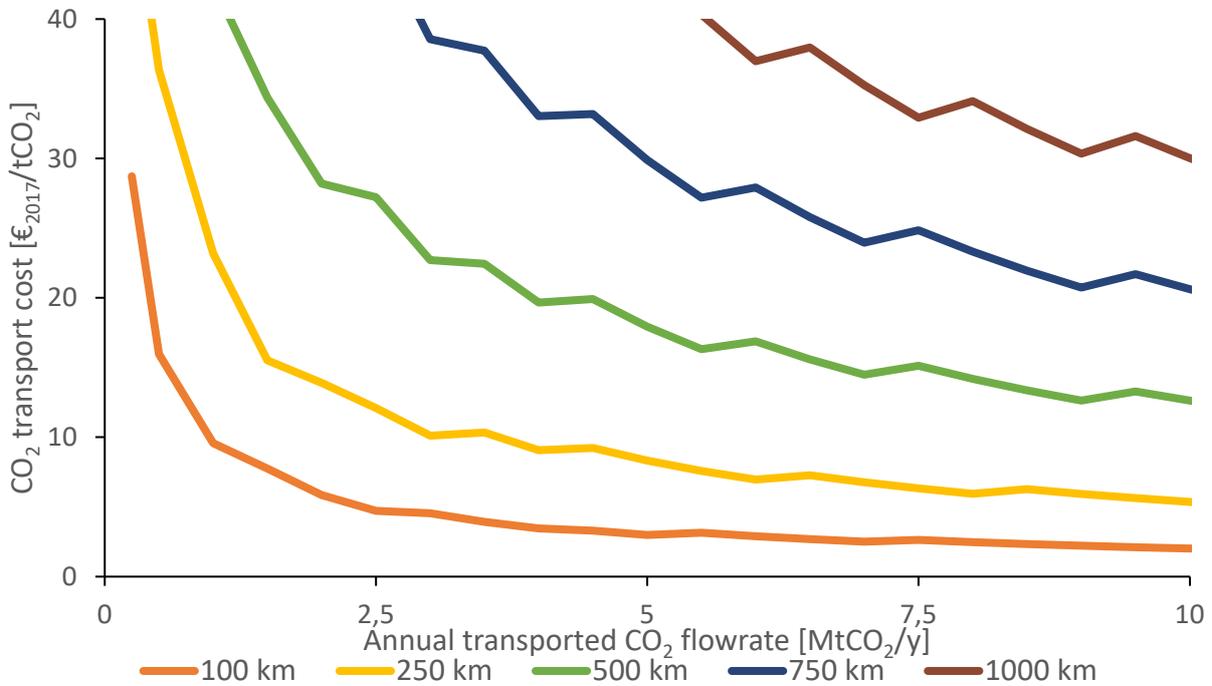

Figure 2-10. CO_2 transport cost via offshore pipeline in function of the annual transported CO_2 flowrate for different transport distances

Figure footnote: Established on the same basis as Figure 2-9 although no offshore reboosting station is considered due to prohibitive cost.
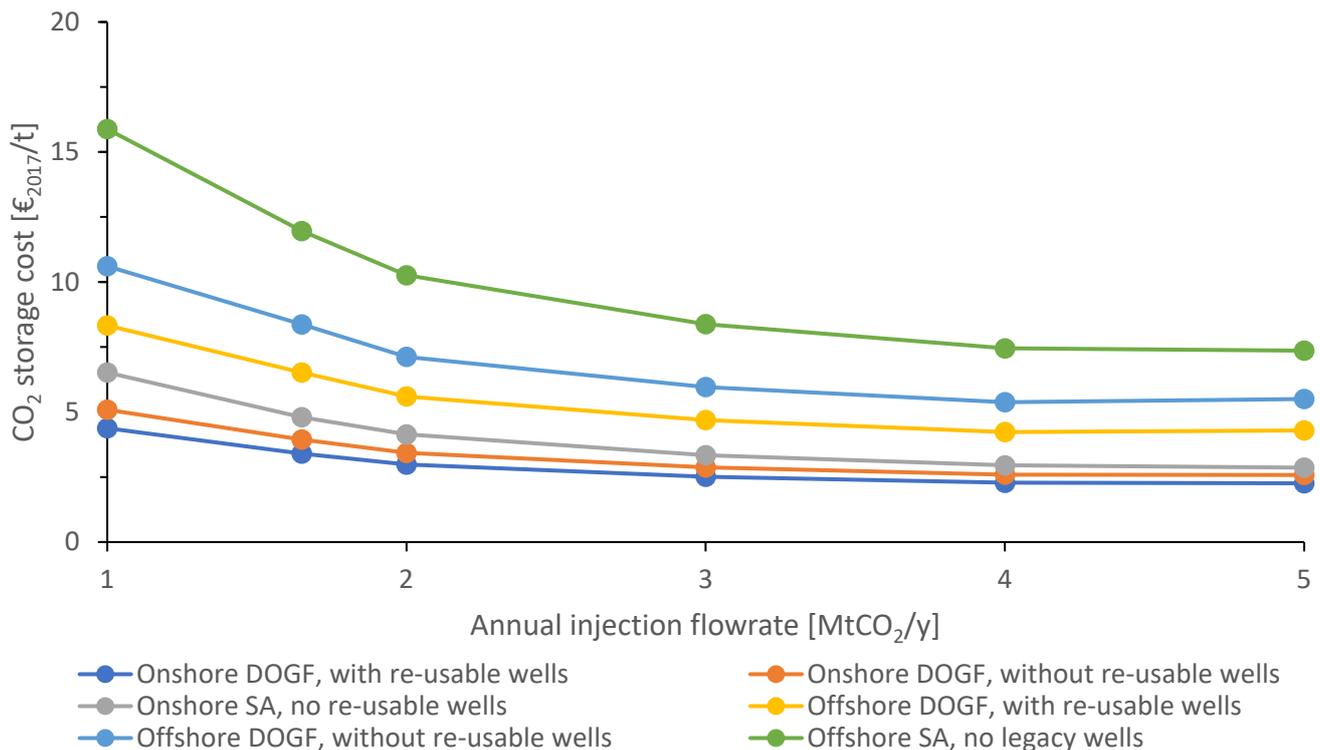
Figure 2-11. CO$_2$ storage cost in function of the annual injection flowrate for different types of storage scenario (DOGF: Depleted Oil and Gas Field, SA: Saline Aquifer)

Figure footnote: Established using the iCCS tool [91, 127] based on the CO$_2$ storage cost methodology established by the ZEP [121]. The cost of an onshore new well is assumed to be 7,3 M€$_{2017}$, while other costs were updated using the IHS Upstream Costs Index [128]. These estimates are based on a project duration of 40 years and a real discount rate of 8%.

In addition to evaluation of CCS from industry based on pipeline transport, it is worth noting that transport of CO$_2$ via ship, and more generally tanked-based solutions (ship, barge, train, truck) is more and more considered for CCS from industry, especially in Europe [129]. Indeed, while pipeline transport has traditionally been the default option considered in CCS-based evaluations, ship-based transport of CO$_2$ can be an attractive option for industrial emitters in some cases, due to its cost efficiency for small CO$_2$ volumes and transport over long distances [125, 130]. Furthermore, shipping typically involves lower upfront investments, shorter construction time, offers more flexibility, could be easier in terms of environmental permitting, and may present opportunities for co-utilisation of infrastructures [131].

Figure 2-12 and Figure 2-13 illustrate the cost of CO$_2$ transport by ship together with pipeline transport costs to indicate when shipping is cheaper than pipeline-based transport. To ensure a fair comparison between pipeline and ship means of transportation, the cost estimates for ship-based CO$_2$ transport also include the increase in conditioning cost compared to a pipeline-based transport. As illustrated, it is worth noting that the cost of ship-based transport is less affected by the annual flowrate and transport distances than pipeline transport. Shipping transport can be the preferred means of transport for a wide range of transport distances especially for small annual flowrates. For example, shipping between harbours would be the cost-optimal option for distances above 250km when transporting an annual flowrate of 1 MtCO$_2$/y, while for higher annual flow rates pipeline transport is more cost-efficient for a wider range of transport distances. While the estimates presented in Figure 2-12 and Figure 2-13 can be used to support better CCS estimates of ship-based chains, more details on when pipeline and shipping transport are most efficient can be found in literature [125, 130].

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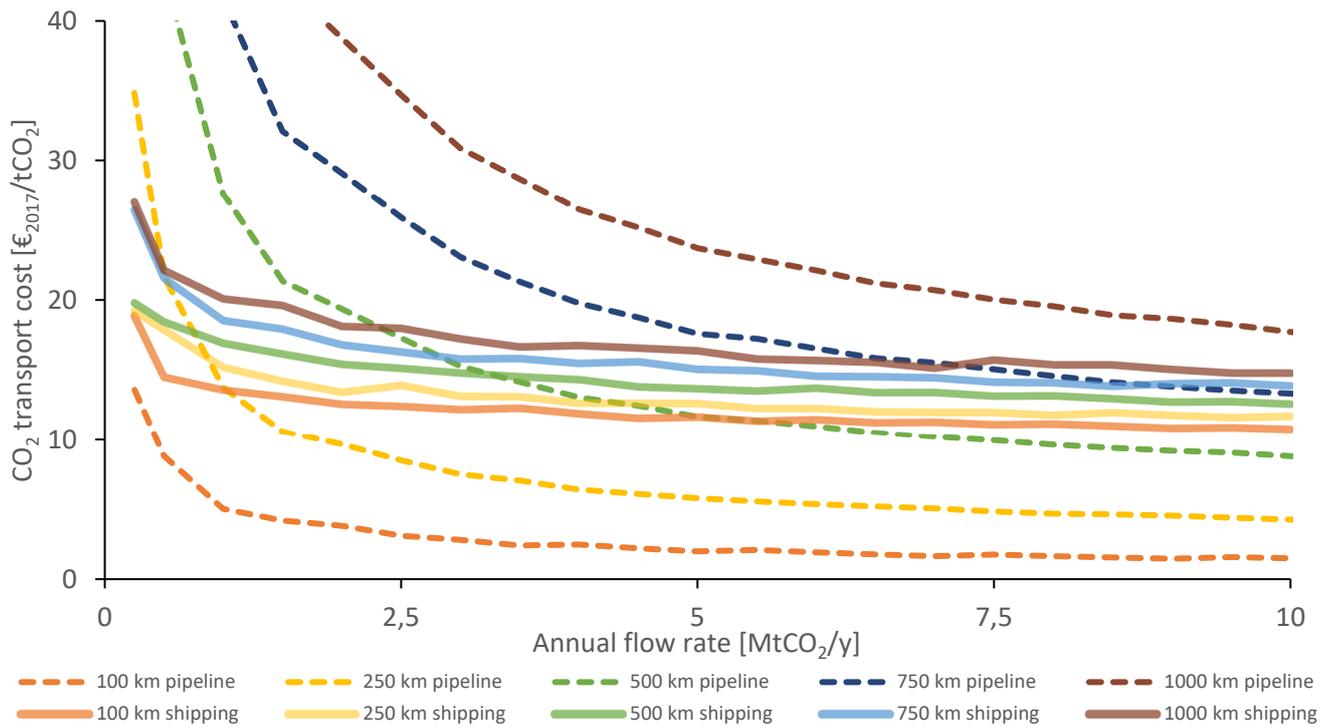
Figure 2-12. CO$_2$ conditioning and transport cost via shipping between harbours in function of the annual transported CO$_2$ flowrate for different transport distances

Figure footnote: Established using the iCCS tool [124, 125] and considering ship costs from Durusut and Joos [132]. The CO$_2$ is considered to be transported at 7 barg, while the optimal number of ships and ship capacity are optimised for each combination of transport flowrate and distance. While the whole cost of conditioning is not included, the increase in conditioning cost compared to pipeline transport is included to ensure a fair comparison between shipping and pipeline transport costs. These estimates are based on a project duration of 25 years and a real discount rate of 8%.
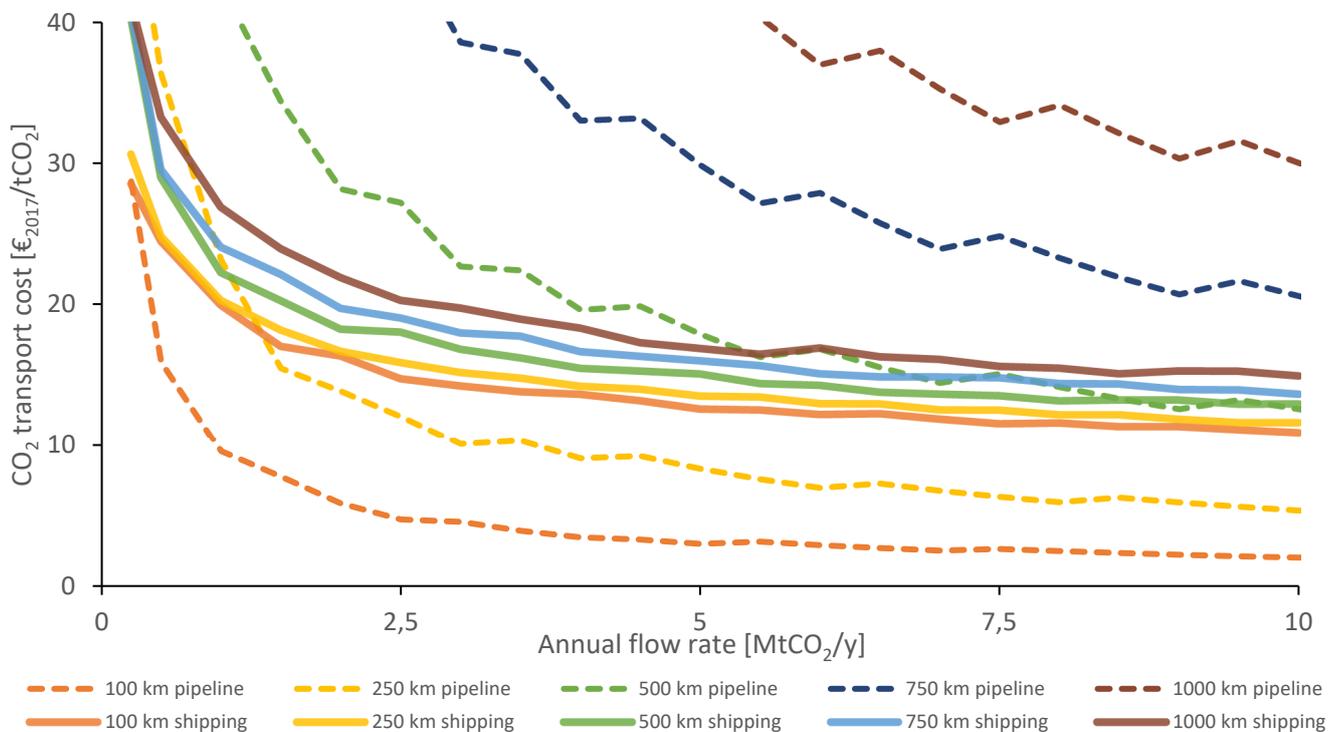

Figure 2-13. CO$_2$ conditioning and transport cost via shipping to an offshore site in function of the annual transported CO$_2$ flowrate for different transport distances

Figure footnote: Established on the same basis as Figure 2-12.

2.3.3.2 Other elements of potential importance

In addition to the issues discussed before, it is worth paying attention to the following elements when assessing the cost of CO_2 transport and storage from industrial emitters:

- Installing pipelines in cramped industrial areas can be costly and time-consuming to construct. In dense industrial sites, excavation work may have to be carried out manually to reduce the risk of damaging other pipelines. Similarly, studies have shown that limited space availability in underground communal pipeline corridors could results in several detours and/or higher operating pressures necessary, which increase local transport costs and possibly prolong license procedures [133].

- Even though high purity CO_2 (>95%) is normally targeted after CO_2 capture, different types and levels of impurities may be present in the CO_2 to be transported and stored. Although these impurities may only be present in small amounts, several studies have shown that the potential associated impurities can have a significant impact on design and cost of CO_2 conditioning, transport, and storage [116, 117, 134, 135]. However, this impact will however depend on the types and levels of impurities present in the CO_2 stream and thus the combination of industrial plant, CO_2 capture technology considered and targeted CO_2 specifications for storage or use [136]. Finally, it is worth noting that there are still some knowledge gaps in term of impact of multi-component impurities on underlying aspects influencing costs of such systems: thermodynamic behaviour, physical properties, corrosion, etc.

- The cost for CO_2 transport and storage can vary significantly by country and region, depending on local costs for rights-of-way, labour, materials and other inputs [137]. Study authors should ensure that cost models representative of the considered geographical region are used. Such models for onshore pipeline transport have been developed by, for example, McCoy [137], Knoope et al. [126], and Wei et al. [138] for the U.S., Northwest Europe and China.

- It is also worth noting that external political and social aspects may also have an impact on transport and storage costs. For example, onshore CO_2 storage has been prohibited in several European countries thus leading in practice to more expensive transport routes and offshore storage [139]. Furthermore, potential social acceptance issues may also impact the routing of the CO_2 transport thus resulting in higher costs. While CCS evaluations shall aim to represent expected conditions taking also these aspects into account, political and social aspects can result in uncertainties which may impact both design and costs.

- Finally, it is worth noting that there could be potential trade-offs between transporting CO_2 and transporting products and raw materials of an industrial plant. In some cases, it could be that CO_2 management costs would change the preferred location of a new industrial plant [85, 140].

2.4 Transferability of experience and technology maturity from power to industry sectors

Technology maturity is an important factor in cost estimates, usually accounted for through process contingency costs as illustrated in Chapter 1 and previously by other organisations like AACE and EPRI [141, 142]. Maturing and operational experience of CO_2 capture technologies has to date been gained primarily through decades of industrial applications in the chemical and petrochemical industries, for processes such as natural gas processing, as well as in small-scale applications at power plants to produce commodity CO_2 for food processing and other industries [143]. Over the past two decades, however, applications of CCS to fossil fuel power plants have been the primary focus of R&D programs and demonstration projects worldwide, resulting in additional experience in that sector. Today, with an increasing focus on CO_2 capture for a broader array of industrial applications, it is important to reflect on experiences from the power sector focus and the extent to which that is transferrable to CO_2 capture from the industrial sector.

The nine-point Technology Readiness Level (TRL) scale, first created by NASA for spacecraft applications, has become one of the most widely-used metrics of maturity of a technology in use by industry [144]. The original NASA descriptions of each level have been modified into a number of general[19] TRL definitions published by organisations such as the European Commission, Electric Power Research Institute (EPRI), DOE, and IEA (see Appendix H). Those TRL definitions have been transferred over sectors and have also been used to measure the development of CO_2 capture technologies. In particular, non-sector specific TRL definitions for CCS or CO_2 capture technologies have been published by the Zero Emission Platform (ZEP) and the EPRI [145, 146], summarized in the first two columns in Table 2-5. Generally, the TRL definitions are based on a scale 1-9, where levels 1-4 consider concept and lab scale, 5-6 consider pilot-scale systems and 7-9 consider larger demonstrations up to full commercial operation. Based on the TRL definitions set out by aforementioned institutes, several terms might lead to confusion, such as the definitions of "relevant", "system", "sub-system", and "component", or the scales, especially in the case of CCS from industry.

The direct transferability of TRLs and experience of CO_2 capture technologies from one sector to another has frequently been implicitly assumed for post-combustion technologies as those are add-on systems downstream the production process. However, the definition of TRLs requires an assessment of the overall system into which a new technology is placed. Thus, the TRL of a capture technology must be defined and evaluated in the context of a specific application, with new applications having lower TRLs. For instance, while chemical absorption with MEA and proprietary solvents have been tested at commercial scale, emerging configurations and/or solvents are -by definition- of lower maturity. The same holds for oxyfuel and pre-combustion capture technologies, as these may require further modifications and integration specific to the industrial process considered.

Essentially, therefore, the transferability of experience or TRL may be limited to the particular CO_2 capture system and application (as described in the TRL definition as "relevant conditions" in Table 2-5). In addition, the concept of System Readiness Level (SRL) in advanced fossil energy applications [147] has been introduced to emphasize that the maturity of new systems depends not only on the stand-alone technology but also its maturity in the specific environment. In the context of CO_2 capture, the concept of SRL allows to reflect that the maturity of a specific capture system is linked to the level of technology development in conditions representative of the targeted industrial application.

While TRLs of different CO_2 capture technologies for the power application have already been assessed [148], these TRLs cannot be directly used on different industrial applications due to the wide range of production processes and their associated characteristics, and the integration of the CO_2 capture system with the industrial core process. Once again, an example of interest is the benchmark solvent, MEA-based chemical absorption process, and improved conventional solvents. These are and will be used, and thus demonstrated, at large-scale for several types of industrial applications in the coming few years. This is, for example, the case in the Abu Dhabi Al Reyadah/Emirates Steel CCS and Longship projects, in the steel and cement industries respectively, amongst others at FEED study stage (BEIS, 2018). In addition, the calcium looping and sorption-enhanced water-gas shift (SEWGS) processes, which are at TRL 4-6 in the power sector, are expected to make significant progress on the TRL scale for industrial applications over the next few years. Specifically, calcium looping is planned to reach TRL 7 for cement production through the CLEANKER project [149], while SEWGS should reach TRL 7 for iron and steel manufacturing through the STEPWISE project by 2021 and 2020 respectively [150]. Experience on the CALIX CO_2 separation technology has been transferred from the magnesium production industry (TRL 9) to the cement production and shall reach TRL 7 through the LEILAC project [151].

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[19] The term general here is meant as non-CCS specific.

Table 2-5. Relevant TRL definitions of CO_2 capture systems in existing literature.

TRL	Generic, non-sector specific definition	Non-sector specific definitions applied to CCS				Definition applied to CCS in industrial sectors	
	European Commission, Horizon2020	**Zero emissions platform [145]** TRL definition based on NETL and H2020 definition but adapted to expand CO_2 capture and storage.		Electric Power Research Institute [142]		**Industrial process with CO_2 capture** based on H2020 definition but adapted to CCS in industrial sectors[a]	
9	Basic principles observed	Actual system proven in operational environment (competitive manufacturing of full system, at scales of several 100s of MWth or around 1 MtCO2/y stored)	**Full Commercial Application**	Normal commercial service	**Demonstration**	Actual system proven in operational process (with product quality maintained), and competitive manufacturing of full system. Technology is commercially available for the specific industry.	**Full commercial application**
8	Technology concept formulated	System complete and demonstrated at industrial scales of 10s of MWth or 0.1 to 1 MtCO2/y stored	**Demonstration**	Commercial demonstration, full scale deployment in final form		System complete and qualified in operational process (with product quality maintained). First of a kind commercial system is installed and works.	**Demonstration**
7	Experimental proof of concept	System prototype demonstrated in operational environment (industrial pilots operating at 10s of MWth and/or separating 10s of kt CO2/y)	**Pilot**	Sub-scale demonstration, fully functional prototype		System prototype demonstration in operational environment (with product quality maintained). For end-of-pipe technologies this means a full prototype operated with flue gas from operational process. For technologies that are highly integrated with the core process, this means a prototype where all critical sub-systems are fully integrated.	**Pilot**
6	Technology validated in the lab	Technology demonstrated in relevant environment (steady states at industrially relevant environments: pilots in the MWth range and/or separating 1 to 10 kt CO2/y)		Fully integrated pilot tested in a relevant environment	**Development**	Technology demonstrated in environment relevant to operation in the specific industry process (conditions replicating industrial operation) with product quality maintained. Trace elements should be included in flue gas if relevant. Demonstration of the sub-systems affected by the product conditions may be sufficient if the full system is demonstrated at TRL 6 or higher for other applications (e.g. power plants).	
5	Technology validated in relevant environment	Technology validated in relevant environment (pilots operated at industrially relevant conditions at 0.05 - 1 MWth) and/or less than 1 ktCO2/y captured/stored	**Small Pilot**	Sub-system validation in a relevant environment		Technology validated in environment relevant to operation in the specific industry process (conditions replicating industrial operation). Trace elements should be included in flue gas if relevant. Validation of critical sub-systems is sufficient.	**Small pilot**
4	Technology demonstrated in relevant environment	Technology validated in the lab (continuous operated pilots at lab scale <50 kWth)	**Lab/Bench**	System validation in a laboratory environment		Technology validated in lab (continuously operated).	**Lab/bench**
3	System prototype demonstration in operational environment	Experimental proof of concept (pilot testing of key components at small bench scale)		Proof-of-concept tests, component level	**Research**	Experimental proof of concept.	
2	System complete and qualified	Technology concept formulated (basic process design)	**Concept**	Formulation of the application		Technology concept formulated.	**Concept**
1	Actual system proven in operational environment	Basic principles observed		Basic principles observed, initial concept		Basic principles observed.	

[a] Based on background work for technology evaluation carried out in CEMCAP [80, 152].

For guidance on setting TRLs, definitions for CCS in industrial sectors are included in the last two columns in Table 2-5. These definitions include requirements with regards to impact of CCS implementation on product quality, plant maintenance (including start-up/shut-down and unforeseen disturbances to the industrial plant operation), and operation of the CCS system under the specific conditions of the facility (e.g. flue gas composition, temperature, pressure, and considering integration). While little attention has been paid to these aspects in past cost evaluations of CCS from industry, technology maturity is an important element to consider in selecting contingencies for investment assessments (see Chapter 1). Similarly, technology maturity will also impact uncertainties in technical and cost performances [5]. Finally, further work is needed to link contingency cost assumptions to TRL values more explicitly.

2.5 Conclusions

With the increasing interest in CCS to support CO_2 emission reductions from industry, a better understanding of costs is required to support decision-makers and guide research to improve the performance and reduce the cost of promising new options. While extensive studies have investigated the techno-economic performance of CCS applied to industrial sources, wide differences in cost estimates have been observed. While this is due in part to differences in the cases studied and the choice of capture technology, a significant part arises from aspects related to cost assessment methods and assumptions (cost metric definitions, energy costs, retrofitting cost, system boundaries, and other factors). Building on a previous CCS costing guideline papers [6], the present work aimed to contribute to the development of improved guidelines for cost evaluation of CCS from industrial applications. In particular, the following key messages can be extracted:

- Several publicly available, transparent, and detailed techno-economic studies exist for different industrial sectors (e.g. iron and steel, cement, refinery, hydrogen, ammonia/urea and methanol, pulp and board). These studies provide a high level of technical and cost details on the industrial facilities considered, which can be used to strengthen future evaluation of CCS from such facilities. Furthermore, these studies have also performed detailed evaluations of currently available CO_2 capture technologies which can be used as a base case in comparative assessments involving new technologies. However, it is worth noting that most of these detailed studies are based on European locations and that some industry sectors are not yet studied in sufficient detail (e.g. waste-to-energy, offshore oil and gas production facilities, petrochemicals…).

- The same basic cost metrics used for CCS from power plant are relevant to industrial processes, although in some cases these may be calculated differently. Furthermore, a key challenge that might arise in the calculation of cost metrics for industrial plants is that many processes result in multiple products. In such cases, the cost of CCS may need to be allocated across these products when reporting costs on a normalized basis (e.g., cost per unit of product). While different allocation bases (flow, energy, market value) exist to distribute these (or other) costs, there is no standardized methodology currently in use. When possible, it is thus recommended to report CCS costs using more than one allocation method as this will provide insights into the impact of different methods on cost performance.

- The origin and production/supply strategy of the steam and electricity required for the CO_2 capture process may vary considerably on a case-by-case basis and have a significant impact on its cost and associated CO_2 emissions, and thus on the CO_2 avoidance cost. It is recommended that transparent scenarios of realistic (future) heat and power supply strategies are included in cost evaluations and that considered methods and assumptions are explicitly reported. The supply strategy, the cost and associated emissions intensity of a heat and power supply can also be site-

specific and dependent on external parameters such as energy prices, which can change significantly over time. To deal with these uncertainties, analysts are encouraged to develop scenarios for plausible combinations of future energy and carbon prices, so as to clearly understand the impact of possible outcomes.

- Few studies properly account for the cost of retrofitting CO_2 capture from existing facilities. As illustrated in the literature, these costs can vary considerably on a case-by-case basis and should thus be properly accounted in studies assessing retrofit applications of CCS. Particular attention should be paid to the following aspects: economic impact of potentially required plant production stoppages, impacts on the main output product quality and plant operation, flue gas treatment requirements, spatial constraints in plant sites, flue gas interconnection and utilities connection costs.

- Costs associated with CO_2 transport and storage are often assumed to be a fixed unit cost per tonne of CO_2, independent of the expected transport and storage conditions (distance, volume, type of transport and storage). While there is significant room to improve the quality of transport and storage cost estimates, it is recommended that any such estimates be based on at least the applicable CO_2 flowrate, type of transport, transport distance and type of storage. Illustrative literature values are provided to support such preliminary estimates when detailed evaluations are not possible. It is worth noting that these considerations hold for both CCS from industry and power.

- Technology maturity is an important factor in cost estimates, usually accounted for through the inclusion of process contingency costs for different levels of maturity and experience. Caution must be taken, however, when considering transferability of technology maturity from power sector applications to various industrial sectors. Impacts to consider include potential effects of CCS on product quality, plant maintenance, and operation of the CCS system under the specific conditions of the industrial facility.

Finally, the authors strongly recommend that future studies of industrial CCS applications make efforts to better document the adopted costing methodology, assumptions, and data sources, and to incorporate sensitivity analyses and scenarios for key assumptions to increase the usefulness and robustness of cost estimates.

Chapter 3: Toward improved guidelines for uncertainty analysis of carbon capture and storage techno-economic studies[20]

3.1 Introduction

Sound uncertainty analysis is critical to the informed interpretation of carbon capture and storage (CCS) techno-economic analyses (TEA) [8, 153]. It can provide valuable insight into the impacts of assumptions and underlying model structure, and give an indication of model quality and robustness, as well as of how reliable the outputs of modelling studies are or can be. Without uncertainty analysis, the actual meaning and importance of CCS cost results from any techno-economic study are difficult to judge, especially for the target audience of such studies, who are often not involved in their production.

Over the years, many publications on uncertainty evaluation methods and approaches have found their way to the scientific domain (e.g., [154-156]), as have publications on the application of uncertainty analysis to TEA and CCS costing specifically (e.g., [157-159]). However, it is notable that often when uncertainty analysis methods are applied in TEAs, mostly simplified methods tend to be used (e.g., single parameter sensitivity analysis) whereas other (more complex) methods could provide additional valuable insight. Furthermore, new and promising uncertainty methods appear to remain unknown to (or unapplied by) the CCS TEA community. We believe this is partly due to unawareness of the full space of uncertainty analysis options, as well as a lack of guidance on when and how to use such options. Therefore, a critical review of the different options, complemented with guidelines on uncertainty evaluation can i) raise awareness to this issue, and ii) increase the effective and fit-for-purpose use of uncertainty analysis in CCS techno-economic studies, hopefully leading to improved understanding and communication of their results.

Building on a previous CCS costing guideline paper [6], this work sets out to provide a review of, and guidelines on, uncertainty analysis methods for use in CCS TEA. It combines knowledge and experience acquired in academia, research institutes, and non-governmental organizations (NGOs). The overarching goal of this chapter is to advance the sound and fit-for-purpose use of uncertainty analysis in CCS TEA by providing practitioners and users with a reference document of relevant methods, tools, and approaches, and a guideline of when and how to use them. These guidelines do not intend to provide an exhaustive account of every available method, rather to showcase different methods over a broad spectrum that can act as an illustration of the type of methods available. Naturally, these guidelines are equally applicable to TEAs of CO_2 utilisation and negative emission technologies.

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[20] This chapter was authored by Mijndert van der Spek, Timothy Fout, Monica Garcia, Vishalini Nair Kuncheekanna, Michael Matuszewski, Sean McCoy, Joshua Morgan, Shareq Mohd Nazir, Andrea Ramirez, Simon Roussanaly, and Edward S. Rubin. It corresponds to a post-print version of the paper "Uncertainty analysis in the techno-economic assessment of CO_2 capture and storage technologies." Critical review and guidelines for use. International Journal of Greenhouse Gas Control 100, 103113. 2020" published under a Creative Commons license CC BY and is available in open access at https://doi.org/10.1016/j.ijggc.2020.103113. The corresponding author for this chapter is Mijndert van der Spek (e-mail address: m.van_der_spek@hw.ac.uk).

3.2 Scope and background

3.2.1 Audience for this chapter

These guidelines target two types of audiences: techno-economic analysis *practitioners* and the *users* of techno-economic studies (Table 3-1). The first group is composed of people involved in the development, modelling, costing, and analysis of (new) CCS technologies. They will be found mainly in research and development (R&D) agencies, academia, and in industrial organisations.

The second group are the users of TEA studies, as earlier described in Rubin et al., [8]. They are mostly technology (R&D) and policy decision-makers. The purpose for this group is twofold: first to help them gain an understanding of the role of uncertainty and how it may affect assessments of technology performance, and second to provide an overview of available uncertainty analysis methods and their use, so that decision-makers can request TEA practitioners to undertake the specific analysis that may fit their information needs best. A key example of the second group is funding agencies, who on a regular basis need to make informed decisions on funding technology proposals.

Table 3-1. Target audiences for this guideline document

Audience	Government	Industry	NGO's & universities
Practitioners: process developers/modellers, cost engineers and technology analysts in:	• R&D agencies	• Operators • Vendors • A&E firms • Venture capital • R&D organisations	• Academia
Users of CCS techno-economic studies in:	• Policymakers • Analysts • Regulators • R&D agencies • Funding agencies	• Operators • Vendors • A&E firms • Venture capital • R&D organisations	• Environmental • Media • Academia • Foundations

3.2.2 Types of techno-economic analyses and candidate parameter categories for uncertainty analysis

Before venturing into available uncertainty analysis methods, it is worthwhile to provide a rough description of the type of techno-economic models found in today's CCS literature, since different types of studies may require different types of uncertainty analysis. Table 3-2 presents a simplified overview of the types of techno-economic models and parameter categories that can be candidates for uncertainty evaluation (based on an earlier publication [160]). On the one end, there are simplified techno-economic models that, for instance, are used to get a first rough idea of technical and economic feasibility. These models may be based on simple first principles or more black box technology descriptions, and their economics are often derived from future projections of known equipment cost. On the other end of the spectrum are detailed techno-economic studies based on full physical (rigorous) technology models and detailed "bottom-up" cost models, such as the engineering-economic models often used in studies by e.g., the US Department of Energy's National Energy Technology Laboratory (DOE/NETL), the International Energy Agency Greenhouse Gas Programme (IEAGHG), and the Electric Power Research Institute (EPRI). In between, there are more or less detailed technical and economic modelling studies, here called intermediate complexity models, often using, e.g., shortcut models for technology description, and/or partial process design and equipment

lists for costing. The choice for a certain model type may depend on the goal of the study, the availability of data and physico-chemical models, and the technology readiness level (TRL).

Table 3-2 is not meant as an exhaustive list of all parameters that need to be scrutinised, but rather provides an illustration of complexity levels. As the table clearly shows, the more detailed and complex the TEA, the more input parameters and models used, and therefore the more parameters that can, or should, be included in the uncertainty analysis. Also, especially for rigorous process models, it is good practice to investigate the effect of model structure. This, for example, could be reflected in the choice of models for mass transfer, as it may have a large effect on the technical process, and therefore its performance and cost (see e.g. [161, 162] for a discussion on how the choice of mass transfer models is relevant in solvent-based CO_2 capture systems, but it equally applies to other types of capture technology).

Table 3-2. Indicative technical and economic model types and candidate parameter (categories) for uncertainty scrutinization, based on [160].

Model complexity level	Technical models		Economic models	
	Description	Potential parameter categories to scrutinise	Description	Potential parameter categories to scrutinise
Rigorous	Typically, full physical models based on first principles, including detailed flowsheets, mass and heat transfer, detailed kinetics, recycles, etcetera.	Below parameter categories as well as mass & heat transfer models, chemical kinetics models	Typically, detailed economic estimates, based on a detailed equipment list, using individual escalation and/or scaling factors and including all capital and operational costs	All of the below plus individual escalation and/or scaling factors, detailed capital and operational cost factors
Intermediate	E.g., short-cut models, excluding part of the physical description (often mass transfer, heat transfer, chemical kinetics)	Below parameter categories as well as, amongst others, chemical equilibrium models and state parameters (P, T)	E.g., combinations of bottom up and top-down methods, using partial equipment lists and Lang/Hand type escalation factors	All of the below plus equipment sizes, purchased equipment costs, escalation factors
Simplified	Often mass and energy balance models based on literature or experimental results	Mass and energy input and output flows	Typically, top-down cost estimates, e.g., exponent models, using cost estimates from earlier studies	Financial parameters (lifetime, discount rate, etcetera); fuel & consumables cost; scaling exponents

3.2.3 What do the existing TEA guidelines say about uncertainty assessment?

As discussed in the introduction, a comprehensive set of guidelines for uncertainty analysis of techno-economic studies of CCS technologies is currently lacking. Two widely used guideline documents for CCS TEA in general, The DOE/NETL Quality Guidelines for Energy System Studies (QGESS [163]) and the European Best Practice Guidelines for Assessment of CO_2 Capture Technologies [164], provide a note on uncertainty analysis. Both recommend the use of sensitivity analysis to help generate an understanding of uncertainty in input data, financial assumptions, and state of technology development. They, however, limit themselves to the most simple of sensitivity analyses (one-at-a-time sensitivity analysis, see 3.3.3.1), without discussing alternative methods and without providing guidance on how to undertake uncertainty analysis in a methodologically sound way.

The techno-economic studies by organisations such as the IEAGHG or the Zero Emissions Platform (ZEP), are also often used as guidelines for good TEA practice. The IEAGHG studies generally use the standardised IEAGHG techno-economic and financial parameters for their studies (e.g., [37]). The IEAGHG studies generally include sensitivity analyses, aiming to offer a picture of how changes to the standard IEAGHG assumptions could impact CCS costs. The key parameters generally investigated are fuel prices, discount rate, discount rate after plant closure, plant lifetime and CO_2 transport and storage costs, subject to the objective of the study [84, 86, 165]. Recent studies [88] also included assessments of potential techno-economic scenarios, where the authors a) explored technical parameters that can have a significant impact on the CO_2 capture costs; b) provided overviews of the TRLs of the CO_2 capture technologies and their impact on costs, c) highlighted technical differences in the literature which make cost-reviews more challenging and homogenised costs under one unique framework, and d) provided an analysis on the energy assumptions and integration of the CO_2 capture system with the original facility, and its impact on costs. The TEA studies by ZEP only investigate sensitivity to plant efficiency and capital costs [166] for CO_2 capture plants and extends that with operational costs, distance, and utilisation level for CO_2 transport [120]. Only in their CO_2 storage costing study, ZEP also included sensitivities on high-level technical parameters like field and well capacity [121].

The abovementioned guideline documents and techno-economic studies use, what are often called, local sensitivity analysis methods for uncertainty analysis, especially the one-at-a-time, and one-way type of sensitivity analysis (see section 3.3.3.1). Another observation is that these studies mostly focus their sensitivity analyses on economic input parameters (although there are exceptions). When addressing technical parameters, they do so mostly at high level, aggregated, parameters such as power plant efficiency, rather than the underlying technical *input* parameters that might exist in a first-principle process model.

3.3 Uncertainty analysis

3.3.1 Definitions of uncertainty analysis

In the CCS TEA literature, Rubin et al. [8], make a distinction between uncertainty, variability and bias. Therein, the author defined uncertainty to reflect "a lack of knowledge about the precise value of one or more parameters affecting CCS costs" ([8]:187). In this definition, uncertainty exists solely in the value of parameters. Variability was defined to refer "to the different value a given parameter may take on (for example, across a collection of facilities, or at different points in time at a given facility). In this case, the values of the parameters are assumed to be known (or knowable), and thus subject to quantitative data analysis" ([8]:187). This means that the variability of a given parameter can be measured and can thus be quantified by, e.g., a probability density function (PDF). This would be much more difficult (or arbitrary) in the case of uncertainty, where the lack of knowledge (true uncertainty) would hamper defining a precise PDF[21]. Furthermore, the author defined bias to refer "to assumptions that skew an analysis in a particular direction while ignoring other valid alternatives,

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[21] This differentiation between uncertainty and variability relates closely to what is called *epistemic* and *aleatoric* uncertainty in the uncertainty quantification (UQ) literature [167]. The UQ community thus refers to both as uncertainty, but of a different nature. Epistemic uncertainty is also called *reducible uncertainty*, *ignorance uncertainty* or *subjective uncertainty* [168]. Aleatoric uncertainty, on the other hand, refers to *inherent variability* of a quantity of interest or *unpredictability due to stochasticity* [167], indeed equivalent to Rubin's definition of variability [8].

factors or data" ([8]:188), meaning that the outcomes of a study may change when favouring one input parameter value over another.

Other scholars use a wider definition of uncertainty by focusing on all kinds of knowledge or information, rather than only on parameters. For instance, "incomplete information about a particular subject" ([169]:387), "lack of confidence in knowledge related to a specific question" ([170]: 504), and "any deviation from the unachievable ideal of completely deterministic knowledge of the relevant system" ([171]:5). These three definitions all focus on the lack of knowable knowledge, values, or information, and in that way, they are closest to Rubin's definition of uncertainty.

We here adopt a wide definition of uncertainty, that includes both parameter [8, 160, 172] and non-parameter uncertainty (i.e., knowledge uncertainty [173] and uncertainty in the model structure and boundaries: methodological, model structure, and contextual uncertainty [160, 172]). At the same time, we embrace the difference between uncertainty and variability (or epistemic and aleatoric uncertainty), because they play an important role in the selection of uncertainty analysis methods, as we will discuss later.

3.3.2 Purposes of uncertainty analysis

Before outlining different uncertainty analysis methods that are commonly used in CCS techno-economic analysis, we first discuss the different purposes uncertainty analysis may have. The first, straightforward, purpose is to provide insight into potentially different outputs as a result of different input assumptions. This is a way to answer "what if", or, diagnostic, type of questions [3, 174]. A more sophisticated purpose can be to provide an estimate of a certain output happening. This relates more to "what will", or prognostic questions [3, 174], because the model specifies a certain outcome of happening with a certain probability. Related to this, uncertainty analysis can help understand which input parameters influence the model outputs most and should therefore be scrutinised and/or parametrised most thoroughly (for instance, through Factor Prioritisation, FP, [174]). This can help answer the question of "where to put most effort" when quantifying model input values. Conversely, uncertainty analysis may provide insight into the parts of the model(s) that have less influence on the outputs, thereby answering "which parts of the model can we simplify" and providing a basis for model reduction (Factor Fixing, FF [174]). An advanced use of uncertainty analysis is model testing, i.e., testing how a model behaves when fed with extreme parameter values or scenarios. If the model behaves as expected (i.e., provides the expected outputs), it increases confidence that the model structure is correct. If unexpected outputs occur, this may indicate that model equations are incorrect, or incorrectly implemented. Finally, uncertainty analysis can also generate insight into the strength of models and/or the input data fed to them (further discussed in 3.3.4.1), which is of great importance when models are used for policy and decision making.

3.3.3 Established uncertainty analysis methods

This section describes established uncertainty analysis methods, i.e., methods that have well-established principles and that have been commonly used in techno-economic analysis for decades. We start out with a general description of sensitivity analysis and local sensitivity analysis methods and then continue with a description of global (e.g., Monte Carlo based) uncertainty analysis. This section ends with describing pitfalls and good practices for the established methods.

To allow explanation of the different methods, a very simple and generic mathematical representation of uncertainty analysis is introduced in the main text:

$$\mathbf{y} = g(\mathbf{x}) \tag{Eq. 8}$$

Where, g is a techno-economic model (i.e., a mathematical function). Despite the simple representation here, g can be a very complex system of equations solved analytically or numerically. **x** is an array of n model inputs $\{x_1, x_2, \ldots, x_n\}$ and **y** is an array of m model outputs $\{y_1, y_2, \ldots, y_n\}$. We call k the number of parameters out of the set n ($k \leq n$) that are actually varied in a sensitivity analysis. This will suffice the explanation of the methods below. Slightly more comprehensive mathematical representations can be found in Appendix I.

3.3.3.1 Sensitivity analysis

Sensitivity analysis (SA) studies how uncertainty in the output of a model is apportioned to different sources of uncertainty in the input of a model [175, 176]. Its main purpose is thereby to identify which inputs most significantly impact the model, helping to prioritise the effort of a modeller on further quantifying the model inputs, while making the model more robust. The model inputs to which the output is most sensitive deserve the most rigorous quantification; the inputs to which the model is least, or not sensitive, can be allowed less stringent quantification, or can be set to fixed (sometimes even random) value. Below we describe commonly used sensitivity analysis methods used in CCS costing, distinguishing between local sensitivity analysis and global sensitivity analysis. The descriptions are made around three main aspects: definition (what), method (how), and their applicability (when).

3.3.3.1.1 Local sensitivity analysis

By far the most commonly used sensitivity analysis methods are local, meaning that one or more variables are varied around selected base, or nominal, values. This also implies that local methods do not include the uncertainties in the whole solutions space (set of potential outputs) of the model) [28]. The reason for the wide use of local methods is their ease of use and of interpretation of their results. <u>What</u>: Local sensitivity analysis can roughly be divided in three types: one-at-a-time sensitivity analysis, one-way sensitivity analysis, and n-ways sensitivity analysis (scenario analysis, sometimes called N-at-the-time -NAT- sensitivity analysis was excluded from below description, because it is a very special class of uncertainty analysis). The simplest local method is one-at-a-time (OAT) sensitivity analysis [154, 155], where the model output is only evaluated against a minimum and a maximum value of a given input parameter. This is most commonly known as the plus/minus 10% way of varying an input parameter (example in Figure 3-1). An extension to OAT sensitivity is *one-way sensitivity analysis* [155]. Here, one parameter at a time is varied but over its entire predetermined range, sampling multiple points. The added value is that a response to an input becomes visible between its extremes, allowing to also identify potential non-linearities between input and output (see, e.g., the IEA figure [177] in Figure 3-2). One-way sensitivity analysis can be further extended to multiple ways sensitivity analysis (or n-ways sensitivity analysis) [155]. This method varies multiple parameters at a time, and uses for each parameter, a set of different values from its entire range. It has the ability to investigate the model output space as function of many parameters with less runs than would be required when only using one-way-sensitivity. In addition, it is able to show interdependencies between input parameters (Example provided in Figure 3-3).

<u>How</u>: The main methodological step in sensitivity analyses is to choose the perturbations to the nominal value of the parameters under investigation. This is only trivial when input-output relations are linear and there is no interaction between input parameters. For OAT analysis for instance, it is common practice to vary each input parameter with a fixed percentage, e.g. +/- 10%, or +/- 50%. Note however, that in case of non-linear relations a variation of 10%, 50%, or other, may lead to a different ranking of sensitivity to inputs. Alternatively, each parameter can be given a different minimum and

maximum, for instance based on expert knowledge of the minimum and maximum values a parameter can have. From a purist perspective, the former approach (using the same plus and minus) is more appropriate, since the local nature of OAT analysis strictly does not allow a statement of the total variance of output **y** as a function of input **x**. Rather, OAT analysis merely produces a ranking of sensitivity to input parameters when varied close to their nominal value. However, from a pragmatic perspective, it seems illogical to vary all parameters with the same percentage around their nominal value if it is known that their real ranges differ substantially, and the practitioner would like to get a first impression of the maximum range of the output parameters. The methodologically correct use of strict OAT analysis is limited, and there may be good reason to choose another method.

One-way sensitivity analysis in this perspective is more versatile than OAT sensitivity analysis, because it allows to sample multiple perturbations from the input parameter's nominal value. Here, it is advised to choose the minimum and maximum values more widely, and preferably according to known, or realistic, limits. The main choice here is rather how many points to include, and where to sample them. For (or when suspecting) non-linear relations, it is advisable to add more points in those sections of the curve that are likely to show the highest non-linearities. For inputs with a linear relation to output, it would suffice to only use one minimum and maximum values without sampling points in between. These considerations also apply to n-way sensitivity analysis.

An important consideration for the choice of method is its computational cost (i.e., the amount of time that it takes to run an analysis). It also depends on the computing hardware available: the computational cost of running an analysis is much higher for any model on a two-core laptop than on a supercomputing cluster where multiple dozens of cores work in parallel. For OAT, the computational cost can be estimated as $C = 2k + 1$ [155], where k is the number of inputs that is varied. The computational cost of one-way sensitivity analysis is obviously higher than OAT sensitivity analysis: $C = (2 + a)k + 1$, where a is the amount of sampled points in addition to its extremes and the base case. Because n-ways sensitivity analysis varies input parameters simultaneously, its computational cost is typically lower than that of one-way sensitivity analysis. As for one-way sensitivity analysis, C depends on the number of sampled values of each input x_i. In addition, it is more difficult (and thus requires more computational effort) to determine the influence of *individual* parameters when using n-ways analysis. For example, $C = 2k$ to calculate all order sensitivities for generalised min/max full factorial designs, i.e., when only two values (a minimum and a maximum) for each input x_i are sampled; $C = 2k + 2$ to calculate first order (individual), interaction and total order sensitivity indices for min/max full factorial designs [155, 174]. Similarly, when a range of values for each x_i is sampled, the computational cost increases to $C = (2 + a)k$, with a being the amount of sample points in addition to its extremes.

<u>When:</u> Local sensitivity analysis is best used to answer diagnostic, or "what if" type of questions, where it has less use to prognostic studies due to its local nature. It can be used very well for a first and quick screening of influential variables, both in process modelling and economic analysis. In this case it is less relevant if the nature of the input parameter variance is pure uncertainty or rather variability (see above), because we are more interested in a ranking of parameters, than in the actual predicted output of the model. Though being simple, local sensitivity analysis shows some relevant disadvantages. Its main drawback is arguably the inability to estimate the influence of variable interactions (OAT and one-way sensitivity analysis) and non-linearities (OAT sensitivity analysis) [174]. Especially in complex and highly non-linear mathematical models this can lead to a false ranking of importance [154], or to the discarding of inputs as relevant based on their single variable sensitivity, while they may actually be relevant in combination with other parameters. This means

94

that local sensitivity analysis is more suited to simple models (like simple factorial cost estimates) than to complex models (like full physical process models). Also, local sensitivity analysis can be inefficient if k is large and only some input parameters are influential. This is, again, especially the case for computationally intensive models.

In addition to diagnostic questions, local sensitivity analysis can also be very useful to test the model structure, by running extreme cases. If for instance, in an economic model, the discount rate is set to a very high value, the levelised cost of product should also become very high. If this is not the case, the modeller knows there may be a mistake in the model formulation.

3.3.3.1.2 Common pitfalls in (local) sensitivity analysis

The following list provides some common pitfalls, to prevent mistakes in the use of sensitivity analysis for CCS techno-economic analysis and elsewhere:

- Local sensitivity methods are perceived as sufficient, where in reality they may not fulfil the purpose of the study. This, in turn, leads to spending time applying methods that may not generate the answers that are needed, or that are less suitable given a certain scope of the problem/question.
- Showing the sensitivity of (too) many model outputs to the model inputs, thereby confusing the audience of the study [174]. Often only a few output parameters are really interesting and is better practice to show only those, while being transparent on the full number of parameters studied.
- Performing piecewise sensitivity analysis where it is not justified. Piecewise sensitivity analysis examines the model in parts or compartments. Often, uncertainty is propagated through the model compartments in non-linear and interactive ways, and piecewise analysis could therefore provide false insights. Examples could include the piecewise examination of uncertainty in a process model and a cost model, where it might be more justified to investigate the uncertainty of the integrated techno-economic model.
- Using the wrong representation of results for a chosen method. For instance, representing the results of an OAT sensitivity analysis in a spider plot. This may happen if modellers are not familiar with the full range of possible approaches and good practices of graphic representation.
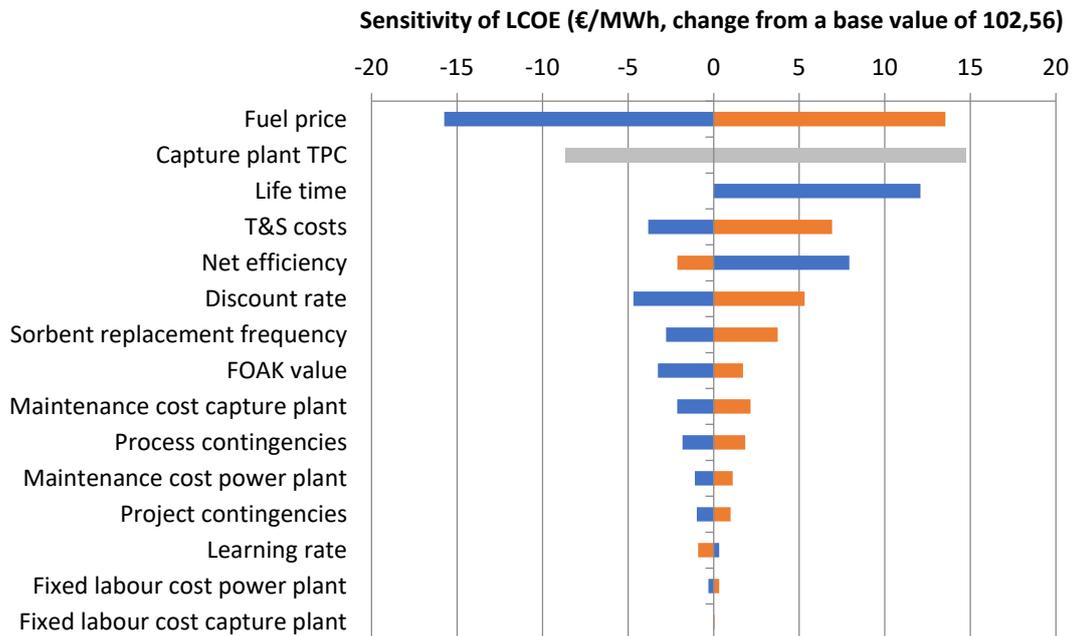
Figure 3-1. Illustrative example of OAT local sensitivity analysis: Tornado diagram representing the OAT sensitivity of the levelised cost of electricity to economic input parameters.

Figure footnote: The case study represents an NGCC plant equipped with post-combustion capture with solid sorbents using an electric swing adsorption cycle [57]. Capture plant TPC ranges (grey colour) include simultaneous variation of the engineering, procurement and construction (EPC) costs, process, and project contingencies, FOAK value, and learning rate, proving a lumped contribution of these capital cost elements.
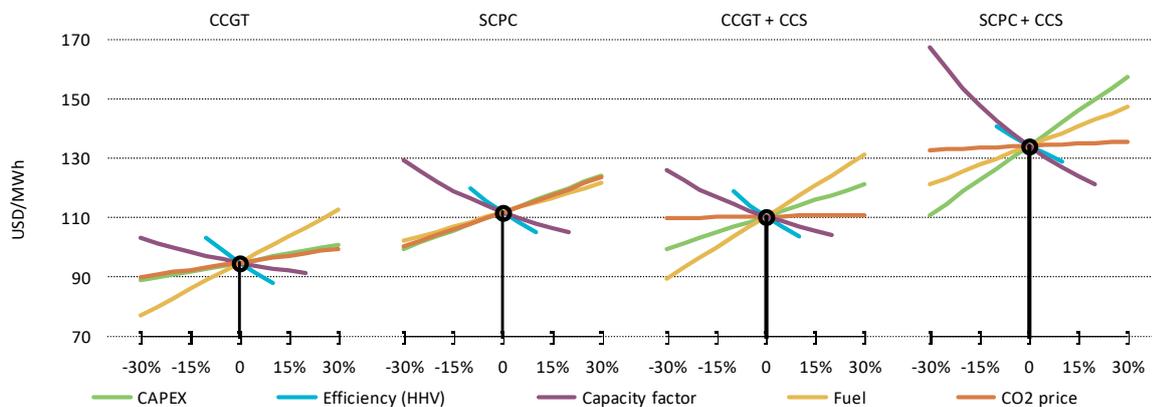
Figure 3-2. Illustrative example of one-way local sensitivity analysis showing the effect of CAPEX, efficiency, capacity factor, fuel costs and CO_2 price on the LCOE of power plant with and without CCS: Figure 5.8 from the IEA Energy Technology Perspectives 2014 [177].

Figure footnote: The parameters were varied independently, leading to the typical spider webs of lines. Note the non-linearity of some parameters, e.g., capacity factor, making one-way analysis more suitable for this parameter than OAT analysis.
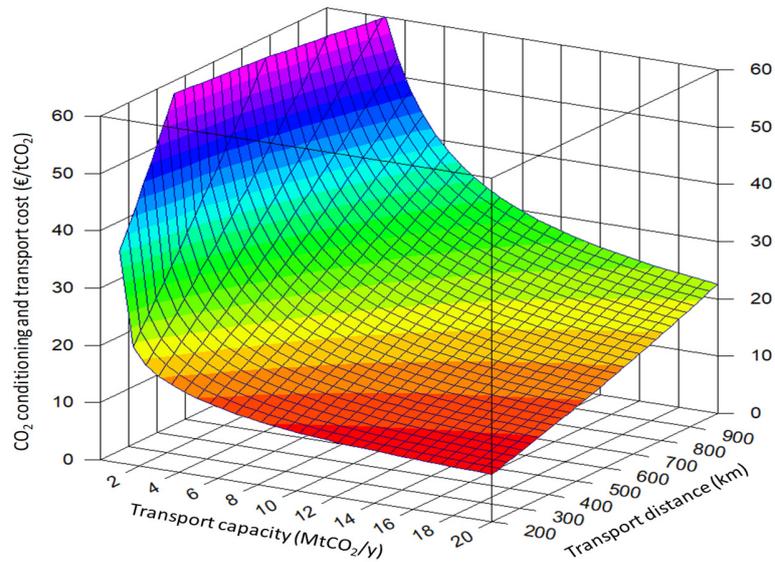
Figure 3-3. Illustrative example of N-ways (here: 2-ways) local sensitivity analysis, based on [125], showing the impact of transport capacity and distance on the cost of CO₂ conditioning and transport for an offshore pipeline infrastructure.

Figure footnote: This figure is based on the following considerations: 1) CO_2 comes from an MEA-based CO_2 capture unit; 2) Pipeline costs are calculated according the CO_2Europipe cost model [178] and an electricity cost of 55.5 €/MWh is assumed; 3) Pipeline diameter is optimised for each combination of transport capacity and distance; 4) A constant utilisation rate of 85%, a project duration of 25 years with an 8% discount rate are considered in the cost calculation.

3.3.3.2   Probabilistic uncertainty analysis

<u>What:</u> Probabilistic (global) uncertainty analysis is a step up from simple one-way or n-ways sensitivity analysis because it assigns a probability to the range of values that a parameter can have [154, 174, 179]. It not only tells something about which values the model outputs **y** may take on as a function of changes in model inputs **x**, but also how likely a certain output may be (for e.g. see Figure 3-4). Global uncertainty analysis can also be used to find the *global* sensitivity of the outputs **y** to the input vector **x**. This is different from *local* sensitivity in the way that the sensitivity indicators are estimated for the whole range of possible inputs and outputs (thus global), while the local sensitivity indicators only apply around the selected base value. Apart from the advantage of understanding the model input-output relationship over the whole range of parameter space, global uncertainty analysis also allows to identify the synergistic effects between model inputs.

<u>How:</u> Probabilistic uncertainty analysis requires assigning to each or some of the input parameters a probability density function. These functions are typically fitted on measured (but often assumed) data. Mathematically, $\mathbb{P}_\mathbf{X}$ are the probability distribution functions of the random vector of input parameters $\mathbf{X} = (X_1, \dots, X_n)$ and $\mathbb{P}_\mathbf{Y}$ the PDFs of the random vector of output parameters $\mathbf{Y} = (Y_1, \dots, Y_m) = g(\mathbf{X})$. This results in a cumulative distribution function $F_Y(y) = \int f_Y(y)$ over the range of output realisations. Preferably, $F_Y(y)$ and $f_Y(y)$ are evaluated analytically, because of low computational cost. Practically, this is often impossible, because the mapping between $\mathbf{X}$ and $\mathbf{Y}$, denominated $g(\cdot)$, is unavailable (i.e., there is no analytical solution for $g(\mathbf{X})$). In such cases, the probability of $\mathbf{Y}$ can be evaluated by repeated sampling using Monte Carlo methods.

From the PDFs of inputs and outputs, global sensitivity measures can be calculated (i.e., the measures that rank the sensitivity of model outputs to each model input), which is now also often done in CCS research. There are different methods to do this and the calculation of these measures is a separate research field (the underlying mathematics can be quite complex and sometimes not transparent). It is beyond the scope of this work to address this in detail, but there are good standard works on calculation of global sensitivity indicators in literature, e.g. [174, 175].

The characterization or quantification of input parameters with PDFs is arguably the most challenging part of global uncertainty analysis and therefore we elaborate a little further on this, without the intention to provide an exhaustive overview of PDF selection. We identify three possible approaches:
1. Hawer et al., [180] developed a guideline based on a flowchart that contains questions to be answered by the user with "yes" or "no", as shown in Appendix J. The flowchart leads the user to a recommendation for a representative uncertainty characterization method for each individual case. The guideline aimed at an audience with little to no knowledge on the terminology and or modelling in the field of uncertainty quantification.
2. In another publication [181], the principle of maximum (information) entropy was suggested. The principle of maximum entropy seeks to choose a PDF that maximizes the amount of information that a distribution can provide, subject to known constraints, as summarized in Table 3-3. This means, for instance, that when only an upper and a lower bound of a range are known, the uniform distribution is the PDF that provides the most information.
3. A third technique for obtaining a PDF is to use a 'subjective' probability distribution, that is a PDF that is based on *knowledge* of the process/parameter rather than *data*. Generally, this is accomplished by the application of formal expert elicitation following a systematic procedure. Examples of formal protocols for expert elicitation can be found in Morgan and Henrion [61], developed for the field of quantitative risk and policy analysis and the IPCC tool linking probability with linguistic descriptions of uncertainty [181].

Table 3-3: Choosing a distributions function using the principle of maximum entropy. Adapted from [181].

Available information	Assigned PDF
Upper bound, lower bound	Uniform
Minimum, maximum, mode	Triangular
Mean, standard deviation	Normal or lognormal if the value physically cannot be below zero
Range, mean, standard deviation	Beta
Mean occurrence rate	Poisson

When: Because of its stochastic nature, probabilistic uncertainty analysis is very capable to answer prognostic, or "what will" type of questions, as well as provide the audience with an answer on how likely such an outcome could be (see also Figure 3-4). It is therefore helpful to policy and decision-makers for strategic decisions and can come to good use in techno-economic analysis of CCS. There are however two large drawbacks that limit the use of probabilistic methods as uncertainty analysis tools. The first relates to the need to describe the variability of the input parameters in probabilistic terms. It requires as a minimum a description of minimum and maximum, but preferably a full PDF. The problem, however, is that the exact values of parameters are often not known (recall the difference between uncertainty and variability, where in the latter case we often do have a good grasp of the variation of values). Randomly assigning probability distributions to inputs can result in misleading outputs. As a result, this would therefore not only not reduce uncertainty, but possibly generate a false sense of certainty and thereby lose its value for answering prognostic questions [155, 160]. It could

however still be useful for answering diagnostic questions or for calculating global sensitivity indicators. Given this consideration, we argue here that probabilistic uncertainty analysis is better suited to deal with *variability*, than with true *uncertainty*.

A second large drawback of, especially, Monte Carlo simulation is that it needs a large amount of runs to become a) statistically significant, and b) to estimate sensitivity indices[22], see e.g. [154, 182]. Such large amounts of runs could be feasible for simple and/or analytical models - like most economic models used in techno-economic analysis - but are a large obstacle for highly non-linear numerically solved models - like rigorous process models.

3.3.3.2.1 Common pitfalls in probabilistic uncertainty analysis

For probabilistic uncertainty analysis, the following additional pitfalls apply:
- Basic Monte Carlo simulation methods assume that input variables are independent of each other, which is often not the case in reality. Ignoring the correlation between dependent variables may lead to a false ranking of influential parameters. To address this issue, a dependence structure (known as a copula) can be created prior to sampling individual uncertain variables [174]. Alternatively, this problem can sometimes be avoided by explicitly modelling the relationship between two variables (e.g., depth and pressure or temperature in a subsurface reservoir model).
- The PDFs of input variables are poorly defined, or are insufficiently definable [155, 160]. Monte Carlo simulation will compile seemingly reliable PDFs of model output regardless the quality of the input distributions. It may therefore create a false sense of certainty for the user of the sensitivity study, that could lead to wrong decisions being taken.

3.3.3.3 Recommended practices for sensitivity analysis and probabilistic uncertainty analysis

As the above sections have shown, sensitivity and probabilistic uncertainty analysis require the rational selection of parameters to vary, how to treat them, and which values, ranges, or PDFs to apply, to perform the uncertainty analysis in a meaningful and efficient manner.

A first good practice then, is to rationally choose the parameters to vary. Initial screening of parameter sensitivity can help reducing the number of varied parameters k and makes the sensitivity analysis more efficient. Alternatively, one can find influential parameters for similar problems in academic or grey literature. When planning to run a Monte Carlo simulation for instance, local SA can be used to discard parameters that are not influential, reducing the required number of Monte Carlo runs. Care should be taken though to also test the sensitivity of parameters when interacting with others, before discarding them altogether. It is good practice to find a balance between the number of parameters to vary and their range. If the range is too wide and/or too many parameters are varied, the results may be less useful and relevant observations may get lost in the mass of output variance, apart from putting too much effort to answering the research question. Especially for probabilistic uncertainty analysis, when the chosen range is too small and/or too few parameters are varied, the results may not be global, thus inconclusive [174].

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[22] For instance, when using a brute force method, the number of model runs N required to calculate variance based sensitivity indicators (like the conditional mean) $E(Y|X_i) = 1000$, then $N^2 = 1000^2$ runs would be required to calculate the sensitivity indices. Even with smart computational methods like Saltelli's [174], the amount of runs required is still $N(k + 2)$ where k is the number of variables to be varied. Linear regression on the Monte Carlo mapping generates sensitivity indicators at lower cost $C = N$, but only calculates univariate (first order) sensitivity indicators (there are other post-processing methods that have this low cost but they have the same drawback, see e.g. [155]).
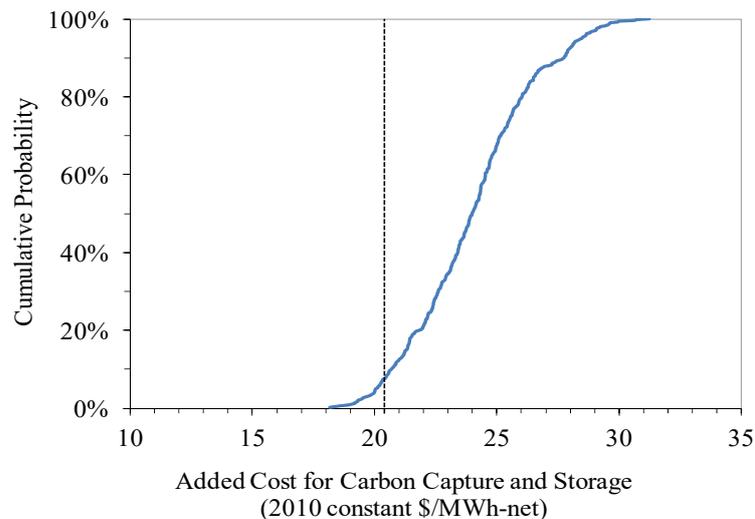
Figure 3-4. Illustrative example of Monte Carlo simulation. Output of a Monte Carlo uncertainty analysis from [179].

Figure footnote: The figure shows both the deterministic (vertical dashed line, no uncertainty) and the probabilistic (solid line) values of the added cost of CO_2 capture for a supercritical coal power plant under the constraint of a 1000 lb of CO_2/MWh gross emission (US) performance standard. For the assumptions of this study there is less than a 10% likelihood of realising the nominal (deterministic) value of added cost. The most likely cost (50% probability) is $24.5/MWh (about 4 $/MWh more than the deterministic value).

A second good practice is to explicitly distinguish between different types of input data (e.g. physical properties versus operational/design conditions/choices, measured data versus expert opinions, economic data versus technical data) or how to cluster them (e.g. a measured value times its weight) [174].

Finally, defining a good "sampling scheme" upfront can save a lot of hassle and unnecessary repetition. Sampling means the amount and values (or positions in a range) of the input data points that are chosen. Sampling can for instance be done by picking random values from a range of possible values, but this may lead to clusters of points and gaps. The modeller can also use random values within subintervals (called stratified sampling) or using particular values within subintervals (also stratified sampling) [174]. Especially for multiparameter sensitivity analysis, several sampling schemes have been developed, focussing on reducing the number of points that need to be evaluated, while remaining a required level of predictive power of the sensitivity analysis. Such sampling schemes are addressed elsewhere, e.g., [174] and include full factorial (only two levels of values: -1/1 or min/max); fractional factorial (FF, only two levels of values: -1/1); Latin Hypercube (LH: multiple levels of values, stratified, needs number of simulations to be larger than the number of varied parameters), or multivariate stratified sampling.

3.3.4   Emerging uncertainty methods

3.3.4.1   Complementary analysis of qualitative uncertainties with pedigree analysis

<u>What</u>: Pedigree analysis is a systematic and harmonised approach to identify and assess knowledge strength in order to minimise subjectivity and increase transparency. It is part of the NUSAP system (Numeral, Unit, Spread, Assessment, Pedigree) for uncertainty assessment and communication proposed by Ravetz & Funtowicz [183]. Generally speaking, pedigree analysis provides an evaluation of the production process of information (how was it measured, derived, theorised?), and investigates

100

the different aspects of the underpinning of the numbers and scientific status of the knowledge used [173], further explained below. Pedigree analysis has key advantages. For instance, it identifies the different sorts of uncertainty in quantitative information and enables them to be displayed in a standardized and self-explanatory way. It also allows to assess the quality of models by increasing transparency on the assumptions and choices and assessing uncertainties in the underlying knowledge base used for building up a process or cost model. Pedigree analysis is flexible in its use and can be used on different levels of comprehensiveness: from a rough sketch to a sophisticated procedure involving structured informed in-depth group discussions on a parameter-by-parameter format. Quite often results are used to develop so-called diagnostic diagrams, which are a convenient way to view each of the key parameters in terms of two crucial attributes: relative contribution to the sensitivity of the output and their strength. Finally, and possibly one of the key advantages, it fosters an enhanced appreciation of the issue of uncertainty in information.

How: Pedigree is expressed using a set of problem-specific criteria that serve to assess different aspects of knowledge strength. It is basically a systematic multi-criteria evaluation of the production *process* of knowledge, therefore looking not only at parameter data but also to knowledge available when building up a model. For example, commonly used criteria are proxy (is something measured directly, or is it estimated using an indirect indicator?) and theoretical understanding (is the data or model based on a well-established scientific theory, or crude speculation?). The type and number of criteria should be tailored to the specific situation.

Assessment of pedigree requires qualitative expert judgment. Expert elicitation systematically makes explicit use of unwritten insights 'in the heads of experts' (e.g., the modeler, or a group of experts), focusing on limitations, strengths, and weaknesses of the available knowledge base. To minimise subjectivity and arbitrariness in the evaluation, a pedigree matrix is used to systematically and transparently transform expert judgment into a numerical scale. A pedigree matrix (Table 3-4) is basically a table with the criteria as columns, and strength scores (typically 0 (weak) to 4 (strong)) as the rows (note that also other scales can be used). In each cell of the table, a linguistic description is provided with the requirements that should be met to receive a particular score. These descriptions therefore serve as yardsticks. Note that these linguistic descriptions are mainly meant to provide guidance in attributing scores to each of the criteria for a given parameter, and as such the descriptions should be tailored to the focus of the study. How clear, explicit and tailormade to the problem the linguistic definitions are, is a key component of the proper and successful application of pedigree matrices. A total score can be then produced for a given parameter or (sub)model (see Figure 3-6). This, however, requires that the modeler (or the experts) weighs the different criteria of the pedigree matrix, for instance by deciding that all criteria are equally important or that some criteria are more important than others. Furthermore, when a group of experts is scoring, total scores of each expert can be aggregated using the median of the expert respondents' scores. Interquartile ranges can then be used as an indicator of inter-expert heterogeneity (degree of consensus/disagreement in the strength of the knowledge base for a given parameter/model). Table 3-4 provides an example of a typical pedigree matrix used to assess the strength of data in a cost assessment of CO_2 capture technologies.

Table 3-4. Example of a pedigree matrix used in the EDDiCCUT project to assess the strength of data input for cost assessment [184].

SCORE	Proxy	Reliability of source	Completeness (only for equipment list)	Completeness (all other parameters)	Validation process
4	A direct measure of the desired quality	Measured/official industrial, vendor, and/or supplier data[23]	Representative data for all line items (processes, instruments, electro, civil, mechanical, etc.)	Complete data from a large number of samples over a representative period	Compared with independent data from similar systems that have been built
3	Good fit to measure	Qualified estimate by industrial expert supported by industry data	Representative data for all process equipment (equipment list, heat and mass balance, PFD)	Complete data from a large number of samples but for unrepresentative periods or from representative periods but for a small number of samples	Compared with independent data of similar systems that have not been built
2	Correlated but does not measure the same thing	Reviewed data derived from independent open literature	Representative data for most important process equipment (equipment list, heat and mass balance, PFD)	Almost complete data but from a small number of samples or for unrepresentative periods or incomplete data from adequate number of samples and periods	Validation measurements are not independent, include proxy variables or have a limited domain
1	Weak correlation but commonalities in measure	Non-reviewed data from open literature	Data from an adequate number of process parameters eat and mass balance, PFD)	Almost complete data but from a small number of samples and unrepresentative periods	Weak and indirect validation
0	Not correlated and not clearly related	Non-qualified estimate or unknown origin	Only high level or incomplete data available	Incomplete data from a small number of samples for an unrepresentative period	No validation performed

Proxy: refers to how good or close a measure of the quantity that is modelled is to the actual quantity one wants to score. *Reliability of source:* evaluates the origin of the collected data. *Completeness:* this criterion assesses the coverage of the data, taking into account the information reported for process inputs, outputs, and associated stressors. It considers not only the amount but also the specific relevance of the presented data. *Validation:* refers to the degree to which data and assumptions used to produce the numeral of the parameter has been cross-checked against independent sources.

Results of the pedigree analysis can be combined with those of a sensitivity analysis in a diagnostic diagram. The diagnostic diagram (Figure 3-5) is based on the notion that neither spread alone (as obtained from a sensitivity analysis) nor strength alone (as obtained from the pedigree score) is a sufficient measure for assessing the quality of a model output. Robustness of model output to parameter strength could be good even if parameter strength is low because the importance of that parameter for the final results may be minor. Alternatively, robust conclusions can be derived for parameters that have large impact on output spread and high parameter strength. Mapping components of the knowledge base in a diagnostic diagram thus reveals the weakest spots and helps in the setting of priorities for improvement.

When: Pedigree analysis can be used for any process or cost evaluation as it increases transparency in the reporting of quality of the data and models used in a given assessment. Such information is important for understanding the robustness of model outcomes as well as to facilitate discussion in expert groups. Furthermore, the use of, e.g., diagnostic diagrams allows for easier representation of the quality and importance of uncertainties. The added value of the approach is especially significant for assessments where there is a weak knowledge base. For instance, technology and costs assessments of technologies that are currently at low TRL level, for which only partial information is available, and significant number of assumptions need to be made regarding performance and scaling.

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[23] Note that vendor or supplier data was in this example score the highest regarding reliability. This of course does not need to be the case, and while carrying out the scoring the modeler (or expert) should take into account whether the data comes from an offer or from a performance guarantee in a contract, the letter being much more reliable.
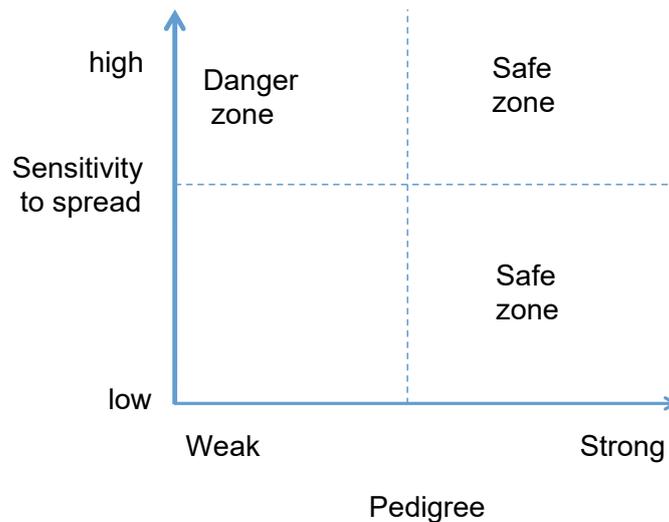
Figure 3-5. Example of a diagnostic diagram for the evaluation of the robustness of the model and model parameters.

Figure footnote: The so-called danger zone is the quadrant containing parameters to which the model output is highly sensitive, but which have a weak pedigree, i.e., the results are dependent on a parameter that is characterized with a weak knowledge base. The safe zones are the two quadrants containing parameters that have a high pedigree. Parameters in the zone characterized with weak pedigree-low sensitivity should be further examined as the low sensitivity to spread could be caused by the assumptions in the knowledge driven by a weak knowledge base.

3.3.4.2   Pseudo statistical approach

<u>What</u>: This approach has been developed in the realm of Life Cycle Assessment (including life cycle costing, see e.g., [185]) but it can be applied to other fields including TEA. The methodology aims to enable the use of Monte Carlo analysis to assess the propagation of uncertainty and/or variability introduced by both uncertainties in data *and* methodological choices into the final results. An example of a methodological choice relevant to this guideline is the allocation of the costs of capture when more than one valuable product is produced in a given system (e.g., polygeneration systems). The key feature of this method (compared to others) is that it explicitly acknowledges large choice related uncertainties on top of parameter uncertainties.

Compared to the natural variability of data, which could be represented through a probability distribution, there is not natural variability in a discrete choice (such as allocation). Although the methodology treats both data and methodological choices in a similar way, the use of the term "pseudo statistical" has the goal of tacitly acknowledging that the use of terminology (e.g. probability, statistical) is not entirely suitable for all cases.

Pedigree scores for technical input data	Proxy	Empirical basis	Theoretical understanding	Methodological rigour	Validation process
SA 2a: H$_2$ unit without CO$_2$ capture					
Feed streams	4	3	4	3	-
Design parameters	3	3	4	4	3
Boundary conditions	4	2	4	3	3
Other physical properties	4	4	4	4	3
SA 2b: CO$_2$ capture unit					
Feed streams	4	3	4	3	3
Design parameters	3	2	3	3	2
Boundary conditions	4	2	4	3	3
Other physical properties	4	4	4	4	3
SA 4a: Conventional polyol					
Feed streams	4	3	4	3	-
Design parameters	3	3	3	2	1
Boundary conditions	4	2	4	3	3
Other physical properties	4	3	4	3	1
SA 4b: CO$_2$-based polyol					
Feed streams	4	3	4	2	-
Design parameters	3	2	3	2	1
Boundary conditions	4	2	4	3	3
Other physical properties	4	2	4	2	0

Pedigree scores for economic input data	Proxy	Reliability of source	Completeness (only equipment)	Completeness (other parameter)	Validation process
SA 1: Naphtha production and transport					
CAPEX	-	-	-	-	-
OPEX	4	4	-	3	0
SA 2a: H$_2$ unit without CO$_2$ capture					
CAPEX	4	2	2	3	3
OPEX	4	3	-	2	0
SA 2b: CO$_2$ capture unit					
CAPEX	4	2	2	3	2
OPEX	4	3	-	2	0
SA 3: CO$_2$ transport and storage					
CAPEX	4	2	1	3	1
OPEX	4	2	-	2	1
SA 4a: Conventional polyol					
CAPEX	4	2	1	3	1
OPEX	4	3	-	2	0
SA 4b: CO$_2$-based polyol					
CAPEX	4	2	1	3	1
OPEX	4	3	-	2	0
SA 5: Chemicals					
CAPEX	-	-	-	-	-
OPEX	3	3	-	2	0

Figure 3-6. Illustrative example of the use of pedigree analysis.

Figure footnote: In [184], pedigree matrices were used in the evaluation of the techno-economic and environmental performance of carbon capture at a hydrogen unit in a refinery combined with CO$_2$ conversion into polyol synthesis. As illustrated, the figures above show pedigree matrices for input data (for the technical model and the cost assessment). The information is provided at the aggregated level of a System Area (each representing group of processes that are part of the value chain under study). Note that the criteria selected for each matrix has been tailored to each type of assessment, for instance, CAPEX and OPEX when assessing data used for costing, and feed streams, design parameters, boundary conditions, and other properties for technical input data. Together with the matrix, the article describes the reasoning behind the choice of scores (which was done by the authors).

<u>How</u>: To be able to introduce pseudo-statistical propagation of a methodological choice, a variable called *methodological preference* (p) (as percentage) is introduced. If there is only one methodological choice, p equals 100%, but if there are different choices (for instance allocating the capture costs based on energy (method 1), mass (method 2), price of the products (method 3)) then each choice is assigned different p values (each between 0 and 100%), with the condition that the sum of all p values equals 100%. In this respect, the pseudo statistical approach is very similar to assigning weights in multi-criteria analysis. As the p values reflect preferences, they are inherently subjective. The methodology therefore allows to explicitly include values (preferences) of stakeholders or to include values that represent trends found in e.g., literature. Compared to other methods, the main advantage is on selecting p values that reflect stakeholder preference or preferences. If literature is used instead, other methods could be used (e.g., analysing discrete cases). The methodological values provided by the experts define the ranges of methodological preferences, such that for each range one methodological choice takes place. The value of a random number from a uniform distribution between 0 and 100 is then generated and evaluated for the ranges of preferences. In mathematical terms, this can be represented as follows:

$$\text{Methodological choice } = \begin{cases} \text{method 1 if } x \in [0, p_1] \\ \text{method 2 if } x \in [p_1, p_1 + p_2] \\ \text{method 3 if } x \in [p_1 + p_2, p_1 + p_2 + p_3] \\ \quad\quad\quad\quad \vdots \\ \text{method n if } x \in [p_1 + p_2 + p_3 + \cdots + p_{n-1}, 100] \end{cases} \quad\quad \text{(Eq. 9)}$$

$$x \sim U\,(0,100)$$

After the parameters are defined, Monte Carlo analysis can then be used for the random sampling to propagate the uncertainty. In the results, the uncertainty introduced by different combinations of methodological choices can then be included. This approach accounts in a pseudo-statistical manner for a representative sample of combinations of methodological choices.

<u>When</u>: The method is particularly recommended when a large number of methodological choices are required (for instance in process modelling and/or costs assessment) thereby avoiding the need for developing one-at the time scenario modelling for choice-related uncertainties, which depending on the number of methodological choices in a given analysis, can become easily very time and resource-intensive.

3.3.4.3   Reduced order models for global uncertainty analysis

<u>What</u>: As mentioned above in section 3.3.3.2, probabilistic uncertainty and sensitivity analysis comes at the expense of many thousands (or more) of model realisations. This may severely hamper their use for computationally heavy models, such as most first principles process models, especially when high-performance computing is unavailable. Therefore, the discipline of global uncertainty analysis has moved towards the use of reduced order models $\hat{g}$ (ROMs, also meta-models, or surrogate models) as a representation of heavy numerical models:

$$\mathbf{y} = g(\mathbf{x}) \approx \hat{g}(\mathbf{x}) = \hat{g}(\mathbf{v}, \boldsymbol{\theta}) \quad\quad\quad\quad \text{(Eq. 10)}$$

Where, $\mathbf{v}$ is a vector of deterministic input parameters and $\boldsymbol{\theta}$ is a set of stochastic input parameters. Different methods of model reduction have been studied and some have found their way to the CCS field of research: Hanak and others have used Artificial Neural Network (ANN) models as surrogates for full physical calcium looping models, and have used these to perform integrated global uncertainty

analysis of the economics of calcium looping systems [159, 186]. Sun et al. [187] used Polynomial Chaos Expansion (PCE) to produce surrogate models of physical models for CO_2 storage well leakage and combined those with risk and cost analysis tools to retrieve stochastic integrated leakage risk and cost information.

How: The reduced order model types for global uncertainty analysis vary, but they all rely on the same approach:

1. Run a limited number (typically several hundreds) of realisations of the full physical model, with uncertainty and/or variability assigned to its inputs (i.e. running different realisations for different combinations of model inputs from predefined parameter ranges).
2. Fit an analytical (e.g. polynomial, ANN, linear regression) reduced order model based on this limited set of model runs.
3. Perform a full Monte Carlo simulation on the ROM. Given that the ROM is analytical, this should take a fraction of the time of a full physical model.
4. Calculate the sensitivity indicators, either directly/analytically when possible or based on the Monte Carlo runs.

The methods to produce some reduced order models and to calculate sensitivity indicators from their probabilistic uncertainty analysis can be quite mathematical and therefore can easily seem daunting to the general techno-economic analysis practitioner. But since the basis of these methods is now well established, also more accessible, ready to use kind of tools are coming available (see section 3.5), which should open up these methods to a wider audience.

When: Previous studies have shown that the used reduced order models are very accurate in describing the input-output combinations of the original physical model within the specified ranges of application [154]. They are therefore very useful when reliable representations of uncertainty and variability are necessary to answer *what will* kind of questions using Monte Carlo simulation, while the original model would be too heavy (computationally intensive) to allow this. They are especially helpful to perform global sensitivity analysis of heavy models, and to aid in factor prioritisation and factor fixing. Like with any probabilistic method however, they are best suited for the variability of input parameters, and less for real uncertainty, given that there may not be a reasonable basis for probability density functions of truly uncertain parameters.

Table 3-5 and Table 3-6 and Figure 3-7 exemplify the use of reduced order models for global sensitivity analysis and the calculation of Variance based (Sobol) sensitivity indicators. The example is based on a series of papers [188-190] in which surrogate models of an MEA capture plant were built based on a full process model and compared with process data from the National Carbon Capture Center (NCCC) in Alabama, USA [191]. Table 3-5 shows the names of the varied parameters along with sources that contain more details of the sub-model development and uncertainty quantification.

Table 3-5. List of parameters for MEA model considered in uncertainty analysis.

Parameter Number	Parameter Name
	Thermodynamic Model (Aspen Plus names in brackets) [189]
1	Gibbs energy of formation at infinite dilution (DGAQFM) for MEA+
2	Gibbs energy of form. at infinite dilution (DGAQFM) for MEACOO-
3	Enthalpy of formation at infinite dilution (DHAQFM) for MEA+
4	Enthalpy of formation at infinite dilution (DHAQFM) for MEACOO-
5	Henry parameter A (HENRY/1) for MEA-H_2O
6	Henry parameter B (HENRY/2) for MEA-H_2O
7	NRTL binary interaction parameter A (NRTL/1) for MEA-H_2O
8	NRTL binary interaction parameter A (NRTL/1) for H_2O-MEA
9	NRTL binary interaction parameter B (NRTL/2) for H_2O-MEA
	Holdup Model [190]
10	H_{L1} (liquid holdup)
11	H_{L2} (liquid holdup)
	Mass Transfer/Interfacial Area Model [190]
12	A_1 (interfacial area)
13	C_L (liquid mass transfer coefficient)

A total of 23 steady-state data sets were generated during the test campaign at NCCC; the propagation of uncertainty was demonstrated for three cases in the previous work [191] and for two additional cases in this paper. Table 3-6 shows the key absorber operating variables for the two cases; the case labels are consistent with the previous work.

Table 3-6. Key operating variables for absorber simulation for two cases

Variable	Case K2	Case K7
Lean Solvent Mass Flowrate (kg/hr)	11794	11791
Flue Gas Flowrate (kg/hr)	2243	2233
Lean Solvent Loading (mol CO_2/mol MEA)	0.247	0.399
Lean Solvent MEA Weight Fraction (g MEA/g [MEA+H_2O])	0.312	0.288
CO_2 Mole Percent in Flue Gas	11.40	9.18
Percent Capture of CO_2	99.49	54.76

The main advantage of developing surrogate models, is the lower computational effort, and therefore the ability to calculate variance-based sensitivity indicators. In this example, this was done in the software platform PSUADE ([192], more information in section 3.5), which allows to calculate Sobol indices [193], which represent a decomposition of variance technique for determining the relative influence of each parameter on the model output. The development of the surrogated model required 1000 runs in Aspen Plus, taking 2-3 hours on a normal desktop machine. Based on these full model realisations, the reduced order model was fitted with Multivariate Adaptive Regression Splines (MARS) [194]. This reduced order model was then run to calculate the normalised Sobol indices in Figure 3-7 for the contributions of the parameters listed in Table 3-5.
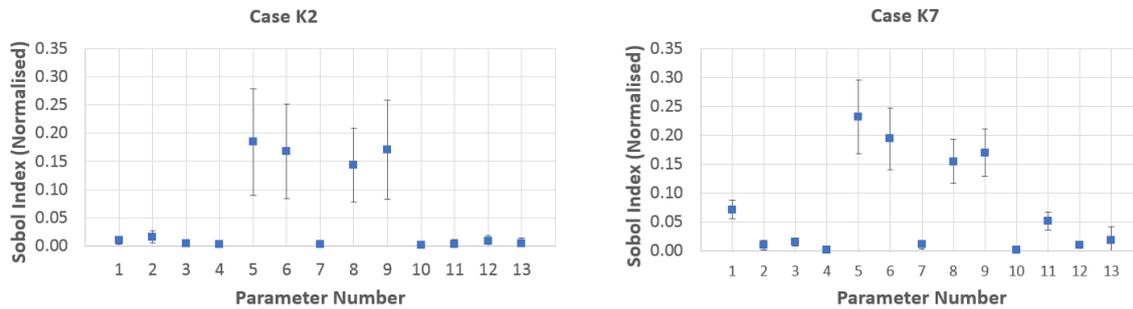
Figure 3-7. Normalised Sobol indices for contributions of individual parameters for two model simulation cases. Points represent mean values and error bars ± 1 standard deviation (n=100 replications performed). Parameter numbers are consistent with those given in Table 3-1

Although the results demonstrate some spread in the values of Sobol indices that results from replicating the calculation, the relative importance is shown to be predicted consistently; for both cases parameters 5-6 and 8-9 are shown to have the highest effect on the CO_2 capture prediction. For Case K2, the packing-related parameters (No. 10-13) are shown to have very minimal effect on the prediction of CO_2 capture. For Case K7, this is not so due to the much higher loading of CO_2 in the inlet solvent, which results in inefficient absorber operation. Although some of the thermodynamic model parameters still have the highest Sobol indices, some of the packing dependent parameters have higher values in comparison to Case K2. As a result, the calculated value of CO_2 capture percentage is not insensitive to the parametrisation of the packing models (mass transfer, interfacial area, hydraulics).

3.3.5   Strengths, weaknesses, and applicability of uncertainty methods to TEA

The previous sections discussed a selection of uncertainty analysis methods available to the CCS techno-economic practitioner aiming to provide basic information on their use. Here, we synthesise this discussion into guidelines on choosing from these methods.

The choice for an uncertainty method depends first and foremost on the purpose of the uncertainty analysis. Recall that we divided these into diagnostic, prognostic, or factor prioritisation/factor fixing and model testing. Additionally, the choice will depend on such criteria including:

- The computational cost of running the model and uncertainty analysis.
- The number and type of input factors that need varying.
- The context of the analysis including the audience.

Note that selection criteria will differ for each user, and also depend on the purpose of the uncertainty analysis, as well as on their experience. Table 3-7 summarises the uncertainty analysis methods in terms of possible selection criteria and suggests TEA areas to which a method may be more or less applicable, while Figure 3-8 provides a general workflow for selecting uncertainty analysis methods. For diagnostic, or "what if" type of questions, local sensitivity analyses often suffice. They present a simple and clear picture of how an output might change as a result of varying one, or multiple parameters, e.g. how the performance and cost may vary as a result of changes in ambient conditions. We recommend the use of one-way or N-way sensitivity analysis, because they provide more information (on non-linear responses) than a standard OAT analysis.

For prognostic, or "what will" type of questions, we strongly recommend global uncertainty methods, provided that the input parameter probability can be quantified satisfactorily. If this is not the case, it

is recommended to avoid prognostic analysis altogether, because there is a danger of creating a false sense of certainty (i.e., the receiver of the model output will see a carefully compiled probability density function, adding to the perception of certainty). However, if the probabilistic output is based on a poor description of input uncertainties, the result is still very weak and may be misleading. The requirement of quantifiable input PDF's implies that what will type of questions should preferably only be answered for CCS technologies and systems that have reached a certain level of advancement, arguably beyond the large pilot plant stage.

For both diagnostic and prognostic questions, we recommend complementing the quantitative uncertainty analysis with a qualitative one, like pedigree analysis. This is especially the case when the model and its results are used for policy and/or decision making, because it provides decision makers with information on how robust the model results are, which is indispensable for making informed decisions.

In case of factor prioritisation or factor fixing, sensitivity analysis is required. In the case of very simple (mostly linear) models without many parameter interactions, a local sensitivity method could suffice, where it is arguably advisable to go beyond OAT. However, factor prioritisation and fixing are often most needed in complex models, in which case a global (probabilistic) sensitivity analysis is essential, to also account for second or higher order effects of an input parameter on model output. If the purpose of the uncertainty analysis is model testing, we recommend using single (OAT) or multiple (NAT) parameter local uncertainty analysis. Preferably, the model is subjected to (combinations of) an extreme value of input parameter(s), that should trigger an extreme output (think e.g., of an extremely high cost of energy, which should lead to a very high cost of CO_2 avoided).

Finally, for a non-specialist audience and sometimes even for a specialized audience, it is arguably a poor idea to show results of uncertainty analysis in very advanced (complex) graphs. To best convey the results, simple plots like tornado or spider plots may be more useful than more complex and less commonly used visualizations, e.g., scatter clouds.

Table 3-7. Uncertainty analysis selection guide.

Possible selection criteria	OAT sensitivity analysis	One-way sensitivity analysis	N-ways sensitivity analysis	Global uncertainty analysis (incl. Monte Carlo)	Pedigree analysis	Pseudo statistical approach	Reduced order global uncertainty analysis
Purpose of uncertainty analysis	Understand first order relative ranking/importance of parameters, understand response to extreme input values for single parameters (model testing)	All of OAT plus understand break points, non-linearities	All previous plus investigates interactions and response to extremes of multiple parameters	To quantify the probabilistic variability/uncertainty in the knowledge base and how that impacts an outcome. To foster an understanding of the distribution of uncertainty and/or variability. To quantify the chance of a certain event of happening. To quantify the global sensitivity to input parameters	To foster an understanding of the strength of the knowledge base underlying data or a model	To understand the significance of value-laden choices compared to parameter variation on the model outputs.	To quantify the probabilistic variability/uncertainty of computationally heavy models in our knowledge and how that impacts an outcome. To foster an understanding of the distribution of uncertainty and/or variability. To quantify the chance of a certain event of happening. To quantify the global sensitivity to input parameters
Relative computational cost/time	Low	Low	Medium	Medium - Very High	Not applicable, but requires substantial time for expert elicitation	Medium - Very High	Medium
Pre-processing data	low	Low	Low	high	medium	High	High
Type of uncertainty method	quantitative	Quantitative	Quantitative	quantitative	qualitative	qualitative & quantitative	quantitative
Able to cope with interactions	No	No	Yes	Yes	Not applicable	Yes	Yes
Able to cope with non-linearity	No	Yes	Yes	Yes	Not applicable	Yes	Yes
Target user/ reader	General public	General public	Depends on number of investigated parameters N (the larger the number the more specialized knowledge is required to interpret the results)	Specialist	General public	Specialist	Specialist

Table 3-7. (cont'd)

| Prior knowledge required on parameters to conduct the assessment	Low	Medium	Medium	High	Understanding the knowledge base is the goal of this type of assessment	High	High
Example TEA areas applicable to	Linear cost models, e.g., capital cost factor models	Simple technical and cost performance models without strong interactions between parameters, e.g., exponent models for capital costs	More complex technical and cost models where there are known parameter interactions and non-linearities, e.g. rigorous/first principle process models	More complex technical and cost models where there is enough data to make/select PDF's, e.g., NPV and LCOE models	Any, particularly TEA studies used for policy and decision making and where knowledge is contested or inherently limited (low TRL)	Situations where contextual choices are expected to have an impact.	Highly complex and non-linear process models that are to be directly linked with economic estimates
Limitations (preferably not to be used for)	When strong non-linearities and interactions are expected	When strong interactions between parameters are expected	When the process models are computationally very heavy	When there is too little information on the shape and potential values of PDF's. When the model is computationally heavy	When a large set of input data needs to be analysed	When there is too little information on the shape and potential values of PDF's. When the model is computationally heavy. When there is a limited (or non-existing) number of value-laden choices.	Models that do not need reduction to become computationally feasible
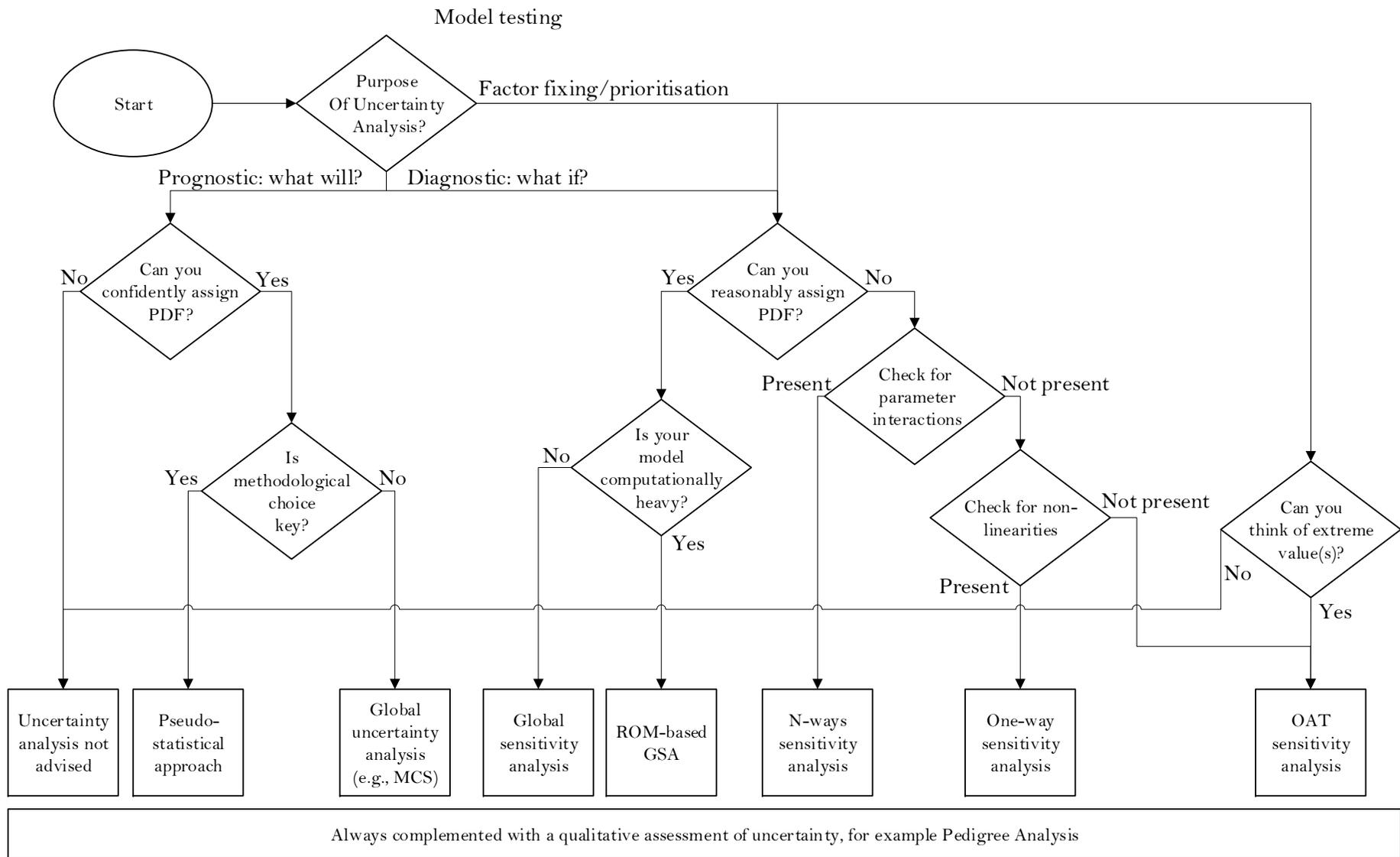
Figure 3-8. Scheme for initial uncertainty analysis selection guidance.

3.4   Advanced uses of uncertainty analysis in CCS TEA

The previous sections discussed guidelines to select and apply methods for sound uncertainty analysis. These methods not only aid the critical analysis of the techno-economic potential of a CCS technology but also points towards specific areas that are candidates for further investigation. There are also, what can be called, advanced uses of uncertainty analysis, for instance in multi-scale modelling for material and system design, design of experimental campaigns in pilot plants that are very expensive, design of CCS supply chains, CCS risk and safety analysis, and use of existing infrastructure in CCS value chain. Two such examples will be discussed here.

3.4.1   Using uncertainty analysis for design of experiments

Bayesian inference is the theoretical foundation upon which intelligent experimental design can be leveraged to inform the models used to characterize a process [195]. When model precision is considered unacceptably low for a process that needs to be further understood, measures should be undertaken to improve understanding of the process [196]. The technique of Bayesian inference, coupled with collection of experimental data, provides a means for reduction of model uncertainty, and thus refinement in understanding for a process systems application of interest. Sequential Design of Experiments (SDoE) is a framework that incorporates uncertainty-based criteria for selection of operating conditions for data collection and the use of the data for refining a stochastic process model in a cyclical manner. The SDoE procedure was previously summarized in Soepyan et al. [197], and demonstrated at pilot scale for a solvent-based CO_2 capture system in Morgan et al. [198]. The SDoE process is represented schematically in Figure 3-9.
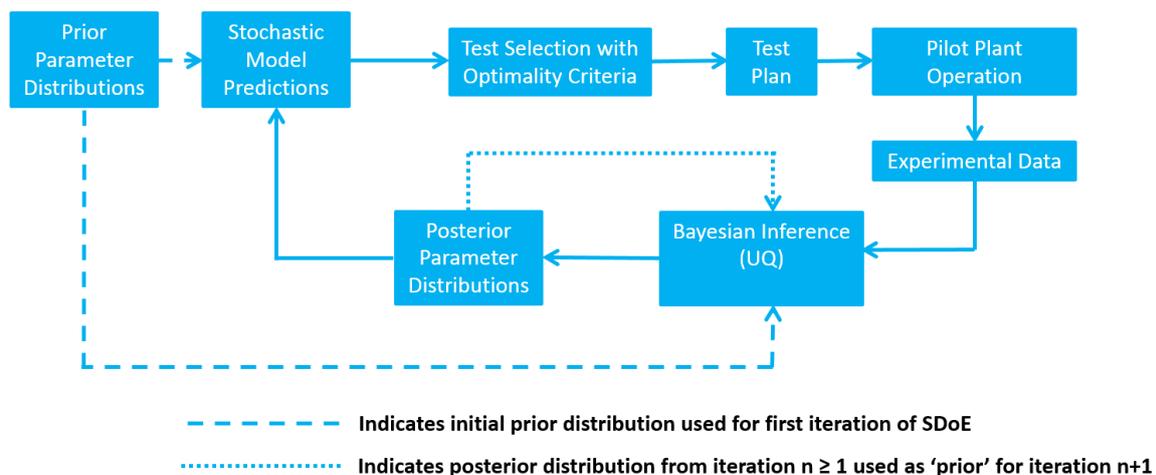
Figure 3-9. Schematic of Bayesian SDoE implemented for pilot plant campaign.

The SDoE methodology requires an initial process model, or a reduced-order surrogate model of the process, in which some of the parameters are characterized by probability density functions (PDFs), representing the parametric uncertainty. For the example of a solvent-based carbon capture system, uncertain parameters may include those related to the physical properties the system, reaction kinetics, and mass transfer and hydraulic models for the packing used in absorption and stripping columns [188-190]. Accurate characterization of mass transfer, interfacial area, and hydraulics, with quantified uncertainty, is necessary for representing the rate-based column models with a specific packing type. For chemical solvent systems, including the

traditional amine-based systems, characterization of reaction kinetics is also essential. Physical properties such as viscosity, density, and surface tension are independent of packing type, although their uncertainties propagate through the mass transfer and interfacial area models, which are dependent upon the property models. However, previous work on physical properties uncertainty quantification for the MEA system for the aqueous monoethanolamine (MEA) system [188], Morgan et al. [189] has demonstrated that the most influential source of property model uncertainty is the thermodynamic framework. Accuracy in the thermodynamic framework is necessary for characterising the vapor-liquid equilibrium in column packing, heat of absorption, heat capacity, and reaction equilibrium constants for chemical systems.

The prior distributions on these uncertain parameters represent initial beliefs about the parameters before collection of data. At various process conditions covering the full operating space of interest, the process model is evaluated stochastically by sampling from the prior distribution of the parameters and calculating the model output for each point in the sample. At each process condition, the model output calculated from all samples may be used to estimate statistics (e.g. mean, variance, prediction intervals) for the model output. For the solvent-based CO_2 capture system example, the operating space of interest represents feasible combinations of input variables including but not limited to solvent flowrate, flue gas flowrate, CO_2 loading in solvent, and CO_2 concentration in the flue gas. Some output variables of interest may include CO_2 capture efficiency in the absorber and reboiler duty requirement in the stripper [191].

Along with the model prediction of uncertainty as a function of the process operating conditions, some optimality criteria [199], which are chosen based on specific experimental goals, are used to select a subset of the candidate set to be included in a test plan for data collection. For example, If a goal of a test campaign is to refine a model by reducing the parametric uncertainty, it may be desirable to collect data in operation conditions where the initial predicted uncertainty is relatively high. Experimental data are collected according to the test plan, and Bayesian inference is used to estimate posterior distributions of the parameters, which represent refined distributions of the parameters conditioned on the data observations. The model prediction of uncertainty is updated (generally reduced) as a result of refinement in the parameter estimates, and this information is used to determine a new test plan for further data collection. This results in the sequential nature of the SDoE process, in which the model is refined over multiple iterations. The decisions regarding the amount of data to collect in each iteration and the criteria for terminating the SDoE loop are left to the experimenter. In practice, however, these decisions may be dictated by limitations in time and money available for pilot-scale test campaigns.

A recent example [200] of SDoE execution for a large pilot-scale test campaign at Norway's Technology Centre Mongstad (TCM) is summarized in the following. In the example here, a Bayesian DoE was applied to an MEA baseline test campaign at Technology Centre Mongstad (TCM). Solvent flowrate, gas flowrate, and lean loading were variables in the test plan, serving as inputs to pre-existing fundamental models which are targeted for refinement using the experimental results. The objective of this experimental campaign was to minimize the maximum uncertainty in the operational space under consideration.

Figure 3-10 below illustrates the results of one DoE iteration for parametric refinement, which results in the following computationally projected improvement in the 95% confidence interval width of the capture percentage projection. Parameters targeted for refinement in this design of experiments related to, among other things, mass transfer characterization which directly affects

equipment size and thus cost. Therefore, improving our understanding of these parameters also improves cost projections.
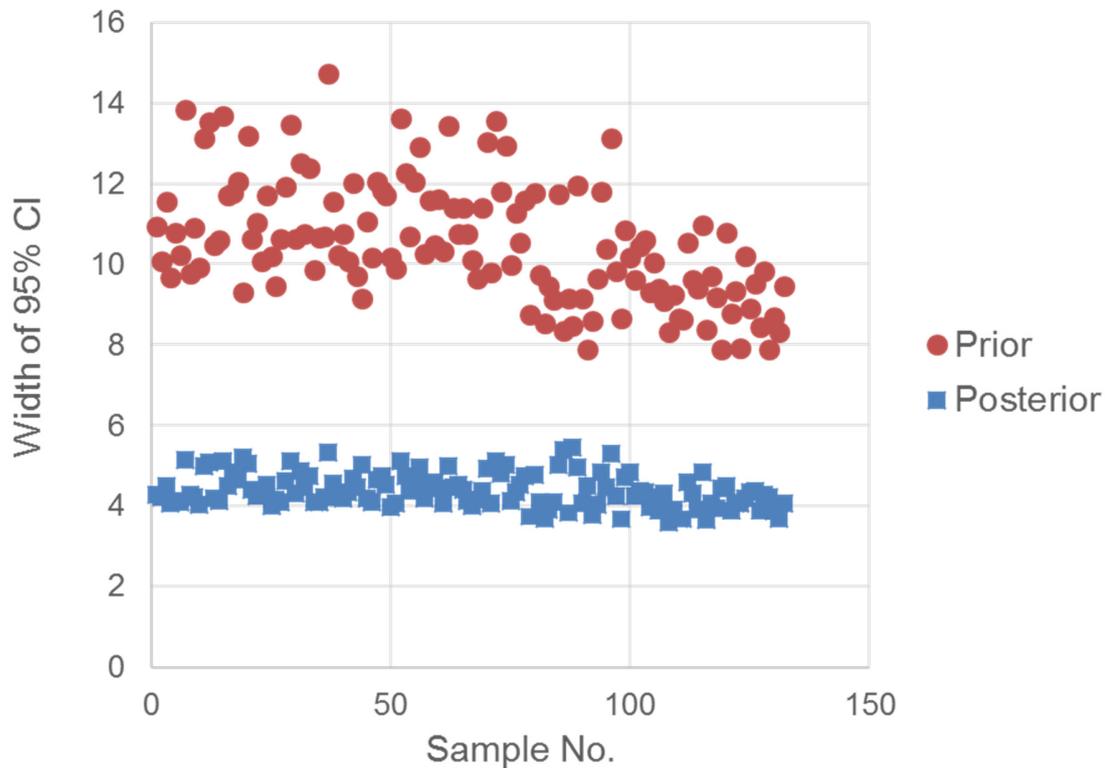
Figure 3-10. Example of results from Bayesian SDoE implemented for an MEA pilot plant campaign at Technology Centre Mongstad (TCM). The reduction in uncertainty (i.e. width of the 95% confidence interval) before and after the campaign is clearly visible.

3.4.2   Design of CCS supply chains under uncertainty

Even though uncertainties can be reduced through technology testing, uncertainties remain an inherent and important element of novel systems with limited large-scale industrial experience and must be taken into account to enable the design of cost-efficient energy systems [8]. Advanced uncertainty quantification approaches, often referred to as 'design under uncertainty' in the engineering field [201, 202], have been developed to account for uncertainty already during the design step to achieve better and more robust designs. In practise, an optimisation layer is added to an uncertainty propagation approach, like Monte Carlo simulation, to optimise system variables according to one or several targeted objective(s) related to the output distribution of key performance indicators (KPIs) as shown in Figure 3-11. The targeted objective(s) can be of different nature. One may want to minimize or maximize the mean value of the probability distribution of a given key performance indicator (KPI). Alternatively, one may aim to minimize the uncertainty range of a KPI distribution or to limit extreme values to reduce associated risks.

While design under uncertainty is being more and more considered in engineering approaches [202-204], only few studies have considered such approaches for design of CCS chains or its components. Cerillo-Briones and Ricardez-Sandoval [205] investigated the robust design of an absorber column under process uncertainties such as flue gas flow and temperature, as well as

115

solvent characteristics. Bjerketvedt et al. [206], investigated optimal ship-based CO_2 transport considering uncertainties in sailing time due to weather conditions, seasonal variations, future fuel cost, and risk of ship breakdown. Similarly, Knoope et al. [207], investigated the impact of price uncertainties on the decision to differentiate or expand investment in a CO_2 infrastructure network using real option analysis. Meanwhile, Roussanaly et al. [208] performed an extensive study on the impact of technical, economic, and system uncertainties on the cost and design of CCS from a waste-to-energy plant.

In the work by Roussanaly et al. [208], one of the considered cases investigated the impact of uncertainties on the design and cost of a CCS chain based on solvent CO_2 capture and a transport and storage infrastructure shared with nearby industries. An optimal design of this chain was developed considering two uncertainty scenarios: 1) "internal" uncertainties such as uncertainties in investment costs, steam, and electricity consumptions; and 2) internal uncertainties combined with uncertainties in the amount of CO_2 captured from the other nearby industries (referred as "external" uncertainties). The evaluation showed that a more robust design could be achieved in the second scenario by optimising the design under uncertainties. A larger pipeline diameter is optimal in the second scenario although it results in a CO_2 avoidance cost 5 €/tCO_2 avoided higher than in the first uncertainty scenario. Indeed, the optimal design of the first uncertainty scenario has a probability of 35% that it cannot accommodate all the CO_2 captured from nearby industries. One of the main drawbacks of design under uncertainty is that it requires significantly more computational time than deterministic approaches, due to the combination of extensive Monte Carlo simulations and the optimisation of multiple variables. Furthermore, a robust modelling of the considered system, as well as a good understanding of the potential underlying uncertainties are required if meaningful results are to be achieved. Despite these challenges, design under uncertainty has shown to provide significant advantages compared to deterministic approaches: enabling cheaper designs or designs that can foster a higher value creation, enabling more robust designs, or limiting risks associated with expected uncertainties. It is therefore important to note that while design under uncertainty modelling approaches can be self-developed, several academic and commercial tools such as UQ lab and Oracle Crystal ball also offer this functionality (see also section 3.5).
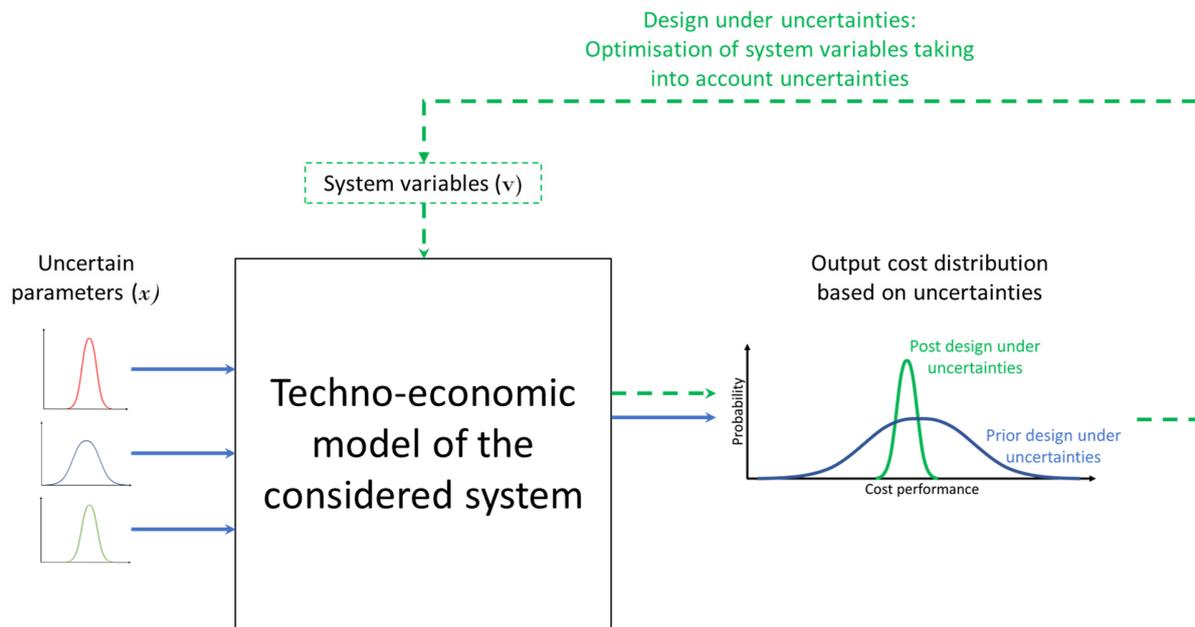
Figure 3-11. Schematic representation of design under uncertainties. The "classical" Monte Carlo simulation process is shown in blue while the additional design element is illustrated in green.

3.5 Available software for uncertainty and sensitivity analysis

With recent interest in uncertainty analysis from many researchers, engineers, and academic institutions, various software packages have been developed to perform uncertainty analysis in a structured manner. The aim of these tools is to provide more accessible, easy, and ready to use software and to facilitate the use of uncertainty analysis to a wider audience. However, selecting a suitable analysis tool for a specific application is not always straightforward: it requires to understand the options' relative merits, features, and performance level. We here try to provide a brief review of the current uncertainty analysis tools can be employed in (CCS) TEAs.

Commercially available tools for uncertainty propagation and sensitivity analysis include Crystal Ball, Pallisade's @RISK [209] and RISK AMP [210]. These three tools are Excel add-in's, which makes them easy to use also to practitioners less versed in programming languages. According to a review by Sugiyama [209], Crystal Ball is the easiest to use due to an excellent user guide and reference manuals, and the provision of a number of illustrative models [211]. All three packages include local and global sensitivity analysis methodologies using post-processing of the Monte Carlo simulations. A limitation of using excel based software for CCS TEA's, however, could be the integration with external software such as MATLAB, Python, or Aspen, which are often used for the process modelling of CCS technologies (this may especially be a limitation for starting TEA practitioners). It should be noted, however, that Aspen includes the capability to perform local SA for process modelling and techno economics, in addition it can be controlled from Excel using the Aspen Simulation Workbook add-in, which then allows the possibility to use these excel based UQ software packages.

In addition to the Excel-based packages, there is a number of recently established tools that have advanced capabilities in performing probabilistic uncertainty analysis. They include, e.g., surrogate-modelling methods such as Polynomial Chaos Expansion (PCE) or Bayesian inference

with the Markov Chain Monte Carlo (MCMC) method[24]. They also include the calculation of local and global sensitivity indicators such as Perturbation, Morris, and Sobol indices and facilitate design optimisation under uncertainty. As a starting point, we name some here that are widely used: the Dakota toolkit is a C/C++ based tool developed by Sandia National Laboratories [212]; UQLab is a MATLAB based framework developed by the Chair of Risk, Safety and Uncertainty Quantification of ETH Zürich [213]; and FOQUS (the Framework for Optimization and Quantification of Uncertainty and Sensitivity), developed by the United States Department of Energy's Carbon Capture Simulation [214], is a Python-based framework that connects to several flowsheeting software using a graphic user interface the United States Department of Energy's Carbon Capture Simulation [192].

Among the discussed software above, the Dakota toolkit provides the most extensive range of UQ methodologies. It has more functionalities than the other two, including for instance methods for quantifying epistemic kinds of uncertainties. It is, however, easy to get lost in all the options it provides and may not be the best software for starting TEA practitioners. The fact that it is written in C++ may also make it difficult to integrate with TEAs. Although all these tools provide extensive manuals and documentation, their use can seem quite daunting, especially if one does not have an advanced programming knowledge. In general, the choice of tool can be based on the programming language preference and most of the tools provide the advantage of being open-source type which allows new methods to be added and integrated. For this reason, it is recommended to start with a tool that provides the best technical guidance, e.g., through the inclusion of interactive procedures or step-by-step checklists. In addition, it is recommended to choose a tool that offers active discussion forums among the user community to help the user with methodological or model implementation issues. Examples include UQLab and FOQUS. Further guidance on the selection of uncertainty analysis tools can be sought for instance through online databases like swMATH. Table 3-8 summarizes the above considerations.

Table 3-8. Comparison of available software packages for uncertainty evaluation of (but not specific to) CCS techno-economic models.

Software name	Crystal Ball	Palisade	Risk AMP	Dakota	UQLab	FOQUS
Type	Commercial	Commercial	Commercial	Open access	Open access	Open access
OAT, One-way and N-ways sensitivity analysis	✓	✓	✓	✓	✓	✓
Global uncertainty and sensitivity analysis (Monte Carlo)	✓	✓	✓	✓	✓	✓
Reduced order global uncertainty and sensitivity analysis	X	X	X	✓	✓	✓
Direct linking with external software (e.g. MATLAB, Python)	X	X	X	✓	✓	✓
Linking with Aspen via Excel interface	✓	✓	✓	✓	✓	✓
Availability of supporting documentation/manual/training materials	✓	✓	✓	✓	✓	✓
Level of programming skills required	None	None	None	Intermediate	Intermediate	Intermediate

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[24]A sampling technique to identify the posterior probability distribution of a parameter once the prior probability distribution has been determined.

3.6 Conclusions and recommendations

Proper use of uncertainty analysis in the performance of CCS TEAs can provide more robust understanding of technical and cost performance to modelling practitioners as well as policy and decision-makers. While there is a growing appreciation over the importance of uncertainty evaluation to both development of models and reporting of results, it remains the case that they are not always evaluated and, when they are, they are often not evaluated using the most appropriate methods. This chapter provided a critical review of a selection of existing and emerging uncertainty analysis methods and provided guidelines on their use. It discussed good practices as well as pitfalls, provided guidance on how to select and use methods, and pointed to sources of further information when outside the scope of this work. It aspires to be a starting point for an audience getting acquainted with CCS TEA, or that wishes to improve their (knowledge of) TEAs.

The review showed that many different methods and approaches to uncertainty analysis exist. We emphasised that key to starting any uncertainty analysis is to first thoroughly define its purpose, and then to ensure that the most suitable type of uncertainty analysis for that purpose is selected (also in relation to the choice of techno-economic model itself). In addition, a good understanding of the methods' strengths and limitations is imperative. Finally, the choice also depends on the existing knowledge of the investigated technology and the associated TEA model and its inputs (including potential parameter ranges – and possibly probability distribution).

The simplest method for model diagnostics ("what If" questions), and one that should as a minimum be applied (in the first instance), is one-at-a-time sensitivity analysis, but we recommend one-way or N-ways sensitivity analysis since most TEAs include non-linearities and parameter interactions. OAT has a really very limited use (although it is actually the most used), except in the case of model testing to extreme inputs, and also then it is arguably better to test the model to extreme scenarios (i.e., combinations of extreme inputs, NAT sensitivity analysis). To address prognostic ("what will") questions, probabilistic methods are most appropriate, but caution must be applied in their use as the distribution of results is only as good as the distribution of inputs. If distributions cannot be quantified with good confidence, then probabilistic methods are simply not suitable to answer prognostic questions (but may still be suitable to answer diagnostic questions). Finally, we highly recommend always complementing quantitative uncertainty analysis with qualitative methods, because they provide insights into the kinds of uncertainty that are unquantifiable, especially relevant to policy and decision making.

In addition to the classic uses of uncertainty analysis, advanced uses can come to the advantage of TEA practitioners and CCS developers. We exemplified that iterative uncertainty analysis can aid the design of experimental campaigns by pinpointing regions that need further investigation, allowing the experiments to be more efficient and less costly. Another advanced use is in the development of CCS infrastructure, where integrating design under uncertainty at the planning stage can enable more robust systems.

The (un)availability of suitable software is something that has hampered (and continues to hamper) the use of more advanced uncertainty analysis in CCS TEA. Although possible, it may be difficult for starting practitioners to combine Excel-based (and very user-friendly) uncertainty analysis add-ins with process simulation software like Aspen (although Aspen does allow local sensitivity analysis on techno-economics within its suite). Further expanding the capabilities of process simulation software to include advanced global uncertainty approaches would be very helpful (the

gProms software has already included this option). For some flowsheeting software, TEA practitioners can link their simulations to existing (and quite elaborate) uncertainty quantification tools in MATLAB or other programming languages, but this requires substantially more knowledge of, and skill in, programming and the software layers underlying process simulation software to make the connection. Easier ways to connect different software would be highly desirable. Also, further improvement of the user-friendliness of existing UQ toolboxes (e.g., by including graphic user interfaces) would aid in the further adoption of advanced uncertainty analysis methods. Finally, a key challenge is to fully combine detailed technical and cost models, to allow for integrated (instead of piecewise) TEA uncertainty analysis.

CCS remains a technology that has had so far limited large-scale implementation and therefore inherently large uncertainties. Uncertainty analysis has, thus, an important role to play in TEA of CCS technologies and systems and there are many opportunities to bring our use of uncertainty analysis to a level higher than currently often done. Hopefully, this work inspires the use of the available possibilities and the continued development towards robust and meaningful CCS TEAs.

Appendix A: Screening questions for FOAK cost estimates

Table A-1. Initial screening questions for design and cost estimates for advanced (pre-commercial) technologies (Based on [47])

No.	Screening question for pre-commercial technologies	How does this affect the FOAK cost estimate?
1	Is the patent and/or intellectual property holder for the technology and/or process involved in this cost estimate?	Without the cooperation of this entity, there can be significant gaps in the cost and design basis estimates.
2	How long has this technology been in development?	The longer the technology has been under development and the more pilot-scale and/or bench-scale operating data that are available, the higher the confidence in the overall cost estimate.
3	What is the intended scale of the technology relative to the size of previous/current installations? (e.g., is the process being scaled up by 10 times? 100 times?) Are there "inflection points" where either the design and/or materials needed for the process become more or less expensive?	The ratio of proposed to current scale of the technology factors heavily into the costing method selected and its accuracy. E.g., a large ratio in a factored cost estimate is typically coupled with a lower degree of accuracy for the final estimate.
4	What is the size of the closest analogue to this process and can it be utilized as a design and/or cost estimating benchmark?	This heavily impacts the accuracy and applicability of a factored or weighted cost estimate.
5	How would you characterize the current level of maturity of the technology? For example: • Does it have a "proof of concept" prototype? • Has it received Underwriter's Laboratory (UL) certification? • Have investors been sought or secured for its development? Is it owned by a parent company and/or governing entity?	The level of maturity weighs heavily on the targeted level of cost estimate detail and the accuracy bounds on the estimate. For example, FOAK technology has a lower risk level and easier market entry if it is UL certified. However, the cost for certification can range from hundreds of thousands to millions of dollars, depending on technology complexity and testing process results.
6	What are the types and quantities of mass and energy inputs and outputs from the facility?	As with mature technologies, without a detailed list of inputs and outputs there is low fidelity in cost estimates.
7	Does the pre-commercial technology produce any "hazardous" products or outputs from the facility, based on applicable codes? (Examples of hazardous materials that require mitigation measures include: non-potable water contaminated with heavy metals; spent catalyst materials; coal combustion bottom ash and fly ash with levels of mercury, unburned carbon, cadmium, and other heavy metals that exceed regulatory limits.)	O&M costs can be affected significantly by the presence of hazardous wastes. Representative disposal cost is roughly twice that for non-hazardous solid waste (unit disposal rate of ($80.00/ton for hazardous materials vs. $38.00/ton for non-hazardous waste [43].
8	What upstream and or downstream dependencies does the facility rely on to be operational and economically viable? A commercial power plant will likely have a dozen or more upstream entities (fuel suppliers, reagent suppliers, equipment suppliers, contractors, consultants, permitting agencies, etc.) and a similar number of downstream entities (waste product off-takers, independent system operator, discharge permitting agencies, etc.) that must be managed.	The greater the number of upstream and downstream entities the greater the economic risk from exposure to market forces and supplier requirements. Compared to a mature commercial technology, a FOAK facility can be expected to have significantly more equipment suppliers, contractors, consultants, and other personnel over an extended period of time, which could increase the man-hour costs of the project schedule by 2-3 times that of a commercial facility.

	Table A-1. (cont'd)	
9	Is the technology using a chemical reagent or other material that must be continuously or periodically supplied? If so, is it a widely available commercial product, a proprietary product, or a newly developed product?	This can significantly affect the estimated O&M cost. For standard materials, the unit cost of low-volume quantities could be 15-25 percent or more than high-volume quantities typical of a commercial coal power plant. Costs for proprietary or newly-developed products could be substantially higher with greater risk of supply availability.
10	Have the technical specifications for the process been distributed to suppliers or manufacturers for review? If so, do they have the capability and experience to supply the equipment? Are they willing to establish a Master Service Agreement to build the equipment?	Review by industry-aligned manufacturers will help support assumptions regarding potential technology suppliers. Indications that technology requirements are aligned with supplier experience base will improve the fidelity of the design basis and cost estimate.
11	How have the risks associated with design, construction and operation been incorporated into the process design and cost estimate? (see Section 1.4.2.2 for descriptions of risk analysis tools.)	Quantifying these risks is critical to establishing the appropriate direct, indirect, and contingency costs in the estimate. A high-fidelity estimate will require a detailed evaluation of these risks.
12	What cost estimating disciplines apply to the facility (e.g., chemical, civil, electrical, mechanical, and structural engineering; procurement specialists; construction management specialists)?	This influences several elements of the capital cost estimate and is especially important for a detailed (definitive) cost study of a specific project. Disciplines vary with technology and scope of what is included in the FOAK cost estimate.

Appendix B: Location cost factors and other contingency cost guidelines for large-scale energy projects

Table B-1. Geographic location cost factors compared to the Netherlands [37]

Location	Materials Cost Factor	Labour Productivity Factor	Labour Cost Factor	Added CCS Contingency factor*
The Netherlands	1.00	1.00	1.00	10%
Eastern Europe	0.92	1.28	0.40	10%
USA (mid-west)	0.94	0.95	0.92	10%
Canada	1.07	1.12	0.96	10%
South Africa	1.03	2.24	0.70	10%
Australia	1.00	1.23	1.38	10%
India	0.93	2.42	0.26	15%
China	0.77	2.29	0.16	15%
Japan	0.91	0.98	0.68	10%
South-East Asia	0.92	1.78	0.24	15%
South America	0.97	1.54	0.28	20%
Middle East	0.91	1.84	0.24	20%

*This factor refers to additional potential execution risks at a particular location for the implementation of a large CCS project; it must not be confused with project and process contingency costs, which are described in Section 1.3.2 of this report.

Table B-2. Other contingency cost guidelines dependent on level of technology maturity and phase of project development (data from [40, 215])

Level of Project Development[a]	Phase of Project Development[b]				
	Concept study	Scoping study	Pre-feasibility	Feasibility study	Engineering completed
First-of-a-kind project	(All figures are percentages of the project overnight cost)				
Process contingency	50	35	20	15	10
Project contingency	50	35	20	15	10
Total contingencies	100	70	40	30	20
Supplementary funds	50	40	30	20	10
Early-mover project					
Process contingency	25	15	10	5	5
Project contingency	40	30	20	15	10
Total contingencies	65	45	30	20	15
Supplementary funds	30	20	15	10	5
Nth-of-a-kind project					
Process contingency	0	0	0	0	0
Project contingency	30	25	20	10	5
Total contingencies	30	25	20	10	5
Supplementary funds	25	15	10	5	2.5

[a] Project level definitions: <u>First-of-a-Kind</u> means <10 commercial-scale demonstrations worldwide or first demonstration in the project region; <u>Early Mover</u> means >10 and <20 commercial-scale demonstrations worldwide or <3 demonstrations in the project region; <u>Nth-of-a-Kind</u> means >20 demonstrations worldwide and >3 in the project region (Greig, et al., 2014).
[b] Project Phase definitions: <u>Scoping Study</u> = ~1% of engineering effort w/ accuracy of −20/+50%; <u>Pre-feasibility Study</u> = ~10% of engineering effort w/ accuracy of −15/+30%; <u>Feasibility Study</u> = >40% of engineering effort w/ accuracy of −10/+20%. No similar definitions for Concept Study and Engineering Completed [40].

These guidelines were based in part on a review of cost estimates at different stages of ten recent large-scale energy projects whose cost escalations are shown below in Figure B-1. Further details are available in Greig, et al. [40].

FEED = Front-End Engineering and Design
FID = Final Investment Decision
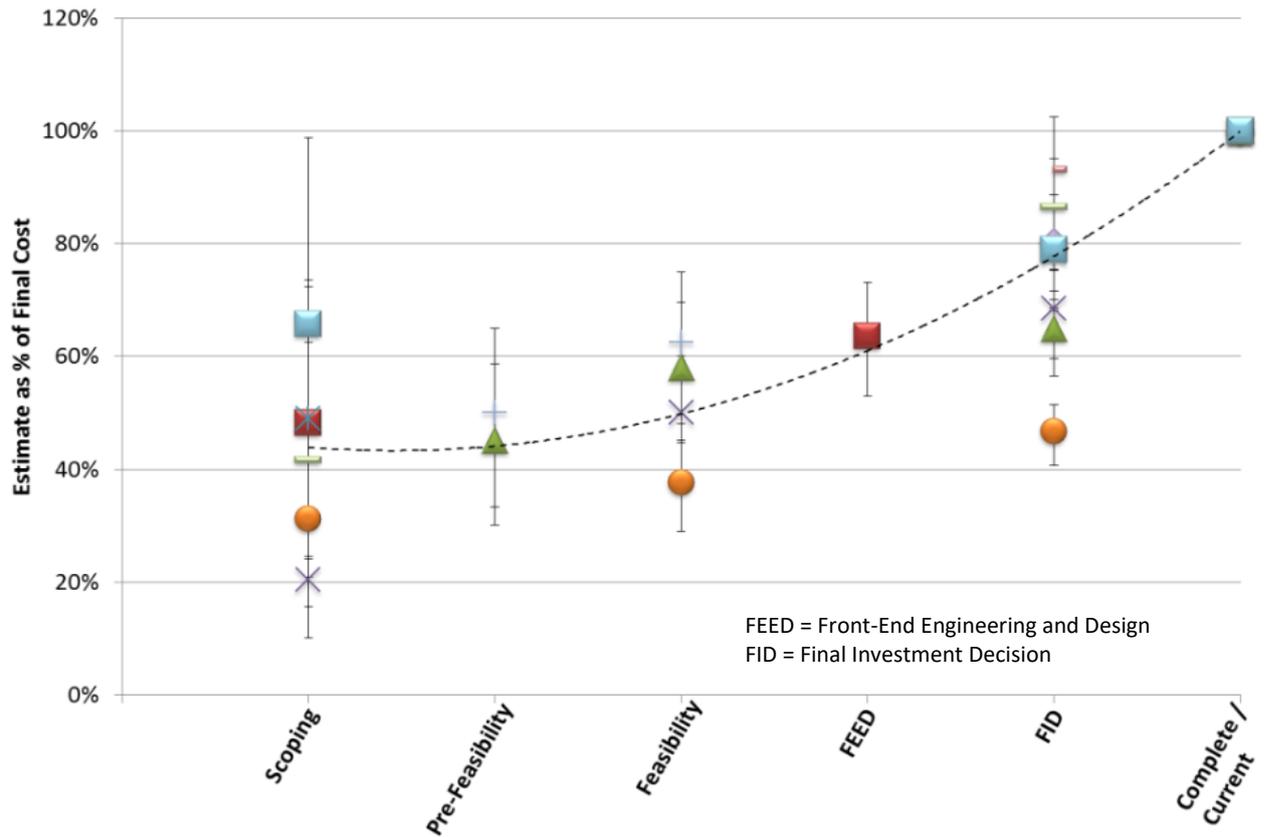
Figure B-1. Illustration of project estimate escalation through the phases of ten greenfield projects untaken during the ten years preceding this study [40]

Appendix C: Example assumptions and results for cost estimates using experience curves

To illustrate the use of experience curves for NOAK cost projections, this appendix shows examples of the assumptions and results reported by IEAGHG [56] for four types of power plants (PC, NGCC, IGCC, and oxyfuel) equipped with carbon capture systems. In that study, the Integrated Environmental Control Model (IECM) was first used to estimate the current cost of each plant on a consistent basis for a U.S. facility with a net power output of approximately 500 MW, a levelised capacity factor of 75%, and a carbon capture system removing 90% of the CO_2 and compressing it to 13.8 MPa. All coal-based plants used a bituminous coal with 2.1% sulphur. All costs were in constant 2002 US dollars) and exclude the costs of CO_2 transport and storage.

These estimates of initial cost were then used to project future costs using technology-specific learning rates, following the methodology outlined in Section 1.5 of this report. Results of an uncertainty analysis also are illustrated in this appendix.

Table C-1. Plant decomposition and sub-section cost allocations for four fossil fuel power plants with carbon capture systems [56]

Plant Type & Technology	Total Plant Costs ($2002)					
	Capital Cost		Total O&M Cost[5]		Total COE[6,7]	
	$/kW	% Total	$/MWh	% Total	$/MWh	% Total
NGCC Plant[1]	**916**	**100**	**38.5**	**100**	**59.1**	**100**
GTCC (power block)	660	72	2.2	6	17.1	29
CO_2 capture (amine system)	218	24	2.4	6	7.3	12
CO_2 compression	38	4	0.2	0	1.0	2
Fuel cost	0	0	33.6	87	33.6	57
PC Plant[2]	**1,962**	**100**	**29.3**	**100**	**73.4**	**100**
PC Boiler/turbine-generator area	1,282	65	5.7	19	34.5	47
AP controls (SCR, ESP, FGD)	241	12	4.1	14	9.5	13
CO_2 capture (amine system)	353	18	7.2	25	15.2	21
CO_2 compression	86	4	0.4	1	2.3	3
Fuel cost	0	0	11.9	41	11.9	16
IGCC Plant[3]	**1,831**	**100**	**21.3**	**100**	**62.6**	**100**
Air separation unit	323	18	1.7	8	8.9	14
Gasifier area	494	27	3.7	17	14.8	24
Sulfur removal/recovery	110	6	0.6	3	3.1	5
CO_2 capture (WGS/Selexol)	246	13	1.6	7	7.1	11
CO_2 compression	42	2	0.3	1	1.2	2
GTCC (power block)	616	34	2.0	9	15.8	25
Fuel cost	0	0	11.6	54	11.6	19
Oxyfuel Plant[4]	**2,417**	**100**	**24.4**	**100**	**78.9**	**100**
Air separation unit	779	32	3.1	13	20.6	26
PC boiler/turbine generator area	1,280	53	5.6	23	34.4	44
AP controls (ESP, FGD)	132	5	2.7	11	5.7	7
CO_2 distillation	160	7	1.4	6	5.0	6
CO_2 compression	66	3	0.5	2	1.9	2
Fuel cost	0	0	11.2	46	11.2	14

Table C-2. Assumed learning rates for power plant sub-sections [56]

Plant Type & Technology	Analogous Technology	Learning Rates					
		Capital Costs			O&M Costs		
		Nominal	Range		Nominal	Range	
NGCC Plant							
GTCC (power block)	GTCC	0.10	0.05 -	0.15	0.06	0.00 -	0.10
CO_2 capture (amine system)	FGD	0.11	0.06 -	0.17	0.22	0.10 -	0.30
CO_2 compression	(same)	0.00	0.00 -	0.10	0.00	0.00 -	0.10
Fuel cost					0.04	0.00 -	0.05
PC Plant							
PC Boiler/turbine-generator area	PC boiler	0.06	0.03 -	0.09	0.15	0.07 -	0.30
AP controls (SCR, ESP, FGD)	FGD/SCR	0.12	0.06 -	0.18	0.22	0.10 -	0.30
CO_2 capture (amine system)	FGD	0.11	0.06 -	0.17	0.22	0.10 -	0.30
CO_2 compression	(same)	0.00	0.00 -	0.10	0.00	0.00 -	0.10
Fuel cost					0.04	0.00 -	0.05
IGCC Plant							
Air separation unit	O_2 prod	0.10	0.05 -	0.15	0.05	0.00 -	0.10
Gasifier area	LNG prod	0.14	0.07 -	0.21	0.12	0.05 -	0.20
Sulfur removal/recovery	FGD	0.11	0.06 -	0.17	0.22	0.10 -	0.30
CO_2 capture (WGS/Selexol)	FGD/SCR	0.12	0.06 -	0.18	0.22	0.10 -	0.30
CO_2 compression	(same)	0.00	0.00 -	0.10	0.00	0.00 -	0.10
GTCC (power block)	GTCC	0.10	0.05 -	0.15	0.06	0.00 -	0.10
Fuel cost					0.04	0.00 -	0.05
Oxyfuel Plant							
Air separation unit	O_2 prod	0.10	0.05 -	0.15	0.05	0.00 -	0.10
PC boiler/turbine generator area	PC boiler	0.06	0.03 -	0.09	0.15	0.07 -	0.30
AP controls (ESP, FGD)	FGD	0.11	0.06 -	0.17	0.22	0.10 -	0.30
CO_2 distillation	LNG prod	0.14	0.07 -	0.21	0.12	0.05 -	0.20
CO_2 compression	(same)	0.00	0.00 -	0.10	0.00	0.00 -	0.10
Fuel cost					0.04	0.00 -	0.05

Table C-3. Estimated current capacity (MW-equivalent) of plant sub-sections [56]

Plant Type & Technology	Current Capacity (MW)
NGCC Plant	
GTCC (power block)	240,000
CO_2 capture (amine system)	10,000
CO_2 compression	10,000
PC Plant	
PC Boiler/turbine-generator area	120,000
AP controls (SCR, ESP, FGD)	230,000
CO_2 capture (amine system)	10,000
CO_2 compression	10,000
IGCC Plant	
Air separation unit	50,000
Gasifier area	10,000
Sulfur removal/recovery	50,000
CO_2 capture (WGS/selexol)	10,000
CO_2 compression	10,000
GTCC (power block)	240,000
Oxyfuel Plant	
Air separation unit	50,000
PC boiler/turbine generator area	120,000
AP controls (ESP, FGD)	230,000
CO_2 distillation	10,000
CO_2 compression	10,000

Table C-4. Effect of key parameter values on cost projections for a PC plant with CO_2 capture [56]

| PC Sensitivity Case	Capital Cost ($/kW)				COE ($/MWh)			
	Learning Rate	Initial Value	Final Value	% Change	Learning Rate	Initial Value	Final Value	% Change
Nominal Base Case Assumptions	0.021	1,962	1,783	9.1%	0.035	73.4	62.8	14.4%
Learning Starts with First Plant	0.013	1,962	1,764	10.1%	0.024	73.4	60.8	17.2%
Learning up to 50 GW	0.018	1,962	1,846	5.9%	0.031	73.4	66.0	10.1%
Current Capture Capacity = 0 GW	0.026	1,962	1,744	11.1%	0.042	73.4	60.9	17.1%
Non-CSS Exp. Multipliers = 2.0	0.029	1,962	1,723	12.2%	0.068	73.4	60.4	17.8%
Coal Price = $1.5/GJ	0.021	1,965	1,786	9.1%	0.035	79.6	68.2	14.3%
FCF = 11%, CF = 85%	0.021	1,963	1,785	9.1%	0.039	57.2	48.2	15.7%
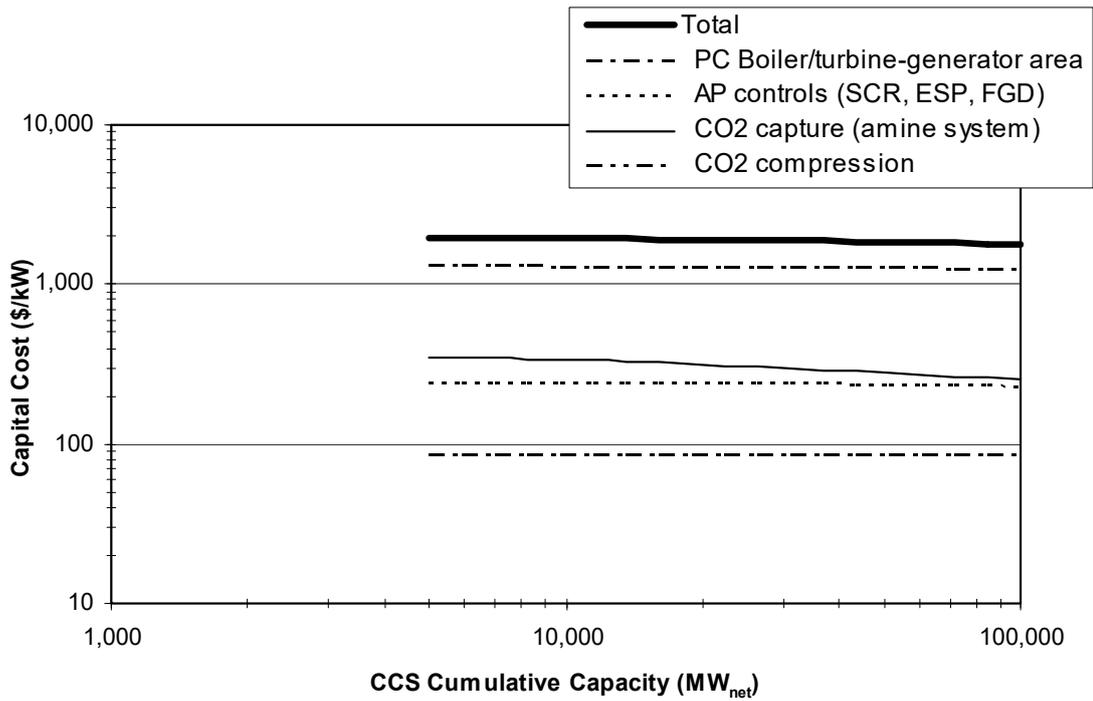
Figure C-1. Illustrative capital cost trends for components of a PC plant with CO$_2$ capture [56]
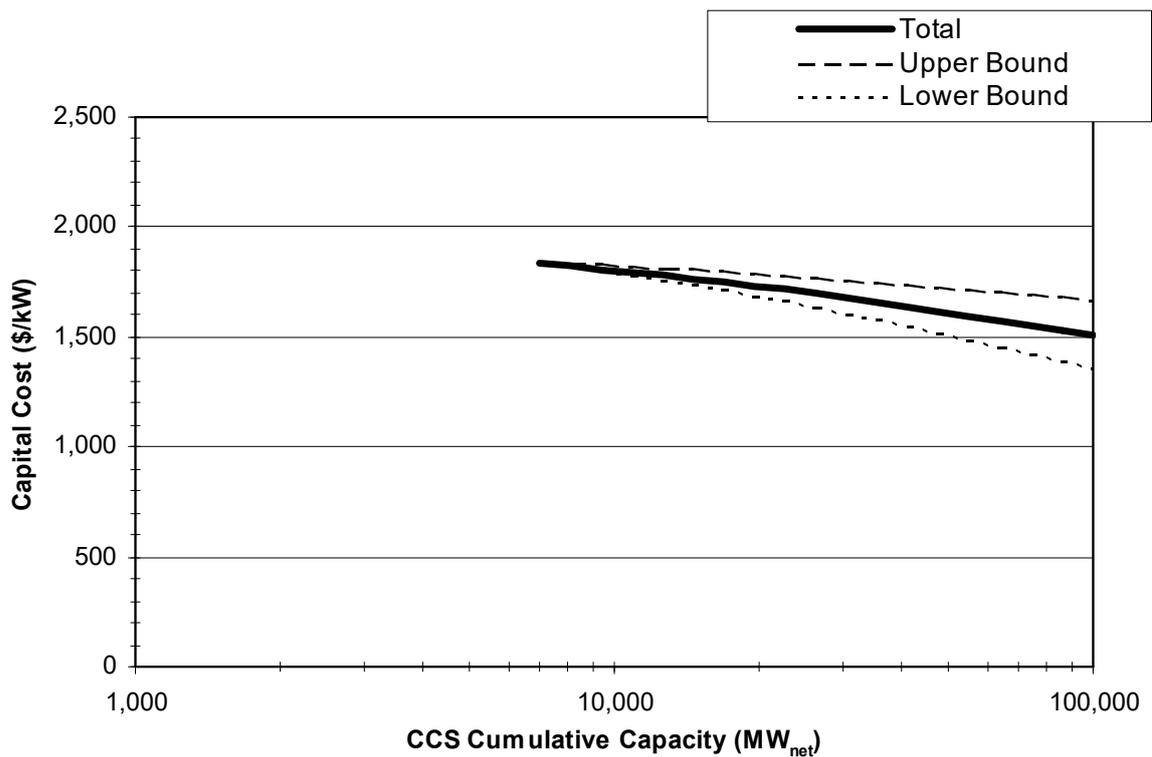
Figure C-2. Effect of learning rate uncertainties on cost projection for an advanced IGCC plant [56]

Appendix D: Example uncertainty in power plant cost using different analysis methods
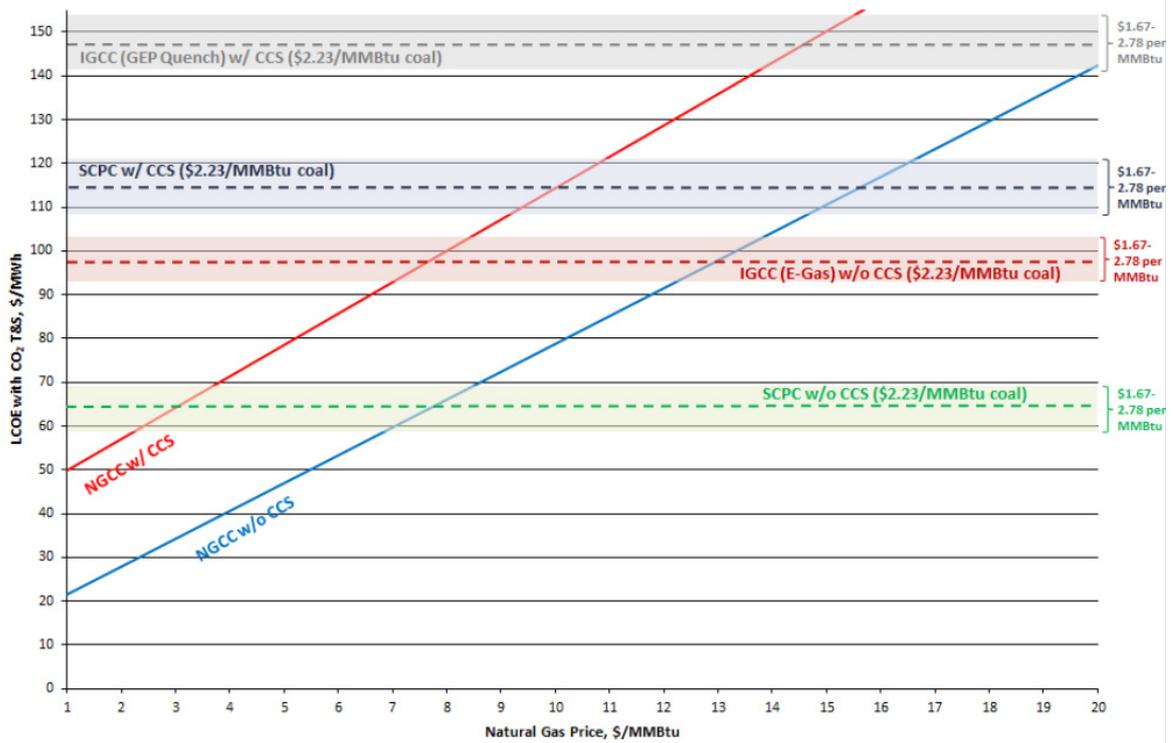
Figure D-1. LCOE sensitivity to fuel costs for NGCC, SCPC, and IGCC plants with and without carbon capture and storage (CCS) [43]
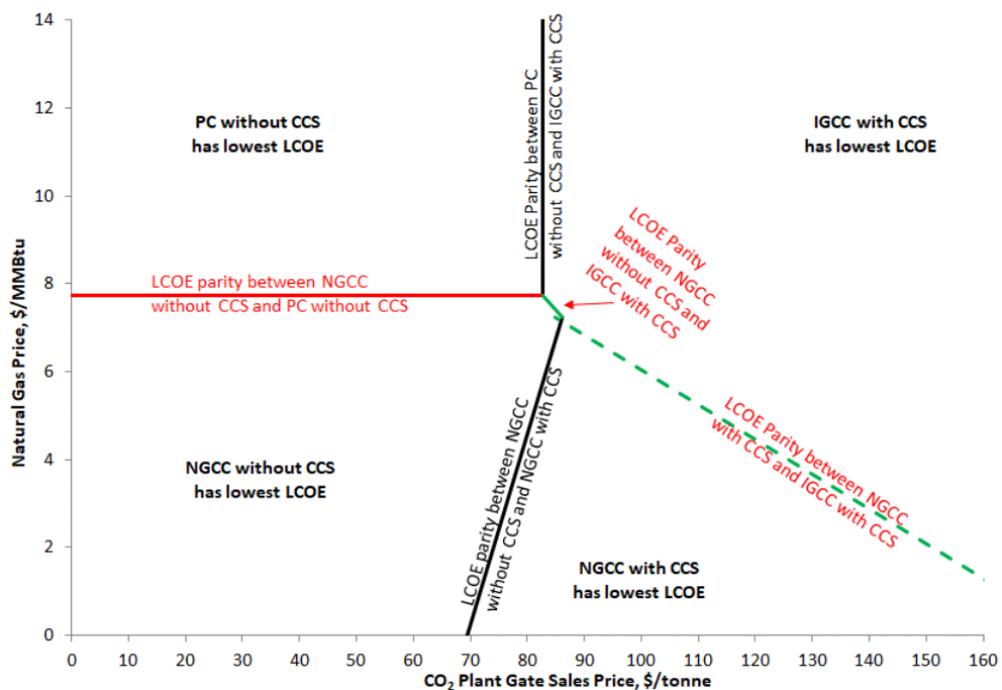
Figure D-2. Phase diagram plot showing the lowest-cost technology options at various natural gas and CO$_2$ sales prices for NGCC, PC, and IGCC plants with and without CCS [43]

**Table D-1. Nominal values and uncertainty parameters assessed for the ammonia-based CO_2 capture system [63]**

Parameter	Units	Nominal (x)	Values (or σ as % of x)	References
Capture System Performance				
Chilling Loads Required at <283°K	Tons Refrigeration	103,000	Normal(x, 10%)	Author Estimate
Chilling Loads Required at 283°K to 302°K	Tons Refrigeration	21,333	Normal(x, 10%)	Author Estimate
Chiller Electrical Use, 276°K Water Product	kW/Ton Refrigeration	0.55	Triangular(0.47, 0.55, 0.60)	[216]
Chiller Electrical Use, 280°K Water Product	kW/Ton Refrigeration	0.47	Triangular(0.47, 0.47, 0.55)	[216]
CO_2 Regeneration Heat Requirement	kJ/kg CO_2	2293	Normal(x, 10%)	Author Estimate
Pumping Head	kPa	207	Triangular(150,207,250)	[217]
Pump Efficiency	%	75	Uniform(70,75)	[217]
ΔP Across CO_2 Capture System	kPa	20.7	Triangular(14,26,30)	[217]
Blower Efficiency	%	75	Uniform(70,75)	[217]
CO_2 Compression, 27.5 bar to 152.7 bar	kWh/kg CO_2	0.03	Triangular(0.028, 0.03, 0.032)	
Capture System Cost				
Reference Chilling Equipment Costs (PFC)	$2007/Ton Refrigeration	441	Uniform(0.7x-1.3x)	Author Estimate
Reference IECM Costs (PFC)	$2007	251.9	Uniform(0.7x-1.3x)	Author Estimate
Reference Aspen Icarus® Costs (PFC)	$2007	59.4	Uniform(0.7x-1.4x)	Author Estimate
CO_2 Absorber Costs (PFC)	$2007	105.1	Uniform(0.7x-2.5x)	[218]
General Facilities Capital	% of PFC	1.57[1]	Normal(x, 10%)	[219]
Eng. & Home Office Fees	% of PFC	9.37[1]	Triangular(0.7x, 1x, 1.5x)	[219]
Project Contingency Cost	% of PFC	16.38[1]	Normal(x, 20%)	[219]
Process Contingency Cost	% of PFC	4.67[1]	Normal(x, 30%)	[219]
CO_2 System Fixed O&M/Year	$2007 Million/year	8.0	Uniform(0.7x-1.3x)	Author Estimate
CO_2 System Variable O&M/Year + TS&M	$2007 Million/year	14.0	Uniform(0.7x-1.3x)	Author Estimate
Plant Financing & Utilisation				
Power Plant Fixed Charge Factor	fraction	0.143	Uniform(0.130, 0.180)	[220]
Power Plant Levelised Capacity Factor	--	0.75	Uniform(0.65, 0.85)	[220]

Appendix E: EIA NEMS model assumptions for power plant learning rates

Table E-1. Learning parameters for new generating technology components in the EIA NEMS model [221]

Technology Component	Period 1 Learning Rate	Period 2 Learning Rate	Period 3 Learning Rate	Period 1 Doublings	Period 2 Doublings	Minimum Total Learning by 2025
Pulverized Coal			1 %			5 %
Combustion Turbine - conventional			1 %			5 %
Combustion Turbine - advanced		10 %	1 %		5	10 %
HRSG[1]			1 %			5 %
Gasifier		10 %	1 %		5	10 %
Carbon Capture/Sequestration	20 %	10 %	1 %	3	5	20 %
Balance of Plant - IGCC			1 %			5 %
Balance of Plant - Turbine			1 %			5 %
Balance of Plant - Combined Cyde			1 %			5 %
Fuel Cell	20 %	10 %	1 %	3	5	20 %
Advanced Nuclear	5 %	3 %	1 %	3	5	10 %
Fuel prep - Biomass IGCC	20 %	10 %	1 %	3	5	20 %
Distributed Generation - Base		5 %	1 %		5	10 %
Distributed Generation - Peak		5 %	1 %		5	10 %
Geothermal		8 %	1 %		5	10 %
Municipal Solid Waste			1 %			5 %
Hydropower			1 %			5 %
Wind			1 %			1 %
Wind Offshore	20 %	10 %	1 %	3	5	20 %
Solar Thermal	20 %	10 %	1 %	3	5	20 %
Solar PV	15 %	8 %	1 %	3	5	20 %

[1] HRSG= Heat Recovery Steam Generator

The NEMS model assumptions above are not accompanied by supporting data and appear to reflect expert judgments based on a review of the experience curve and learning rate literature. In addition, NEMS uses several other factors to estimate future overnight costs, including a "technological optimism" factor—a multiplier of 1.0 or more, applied to the first four units of a new, unproven design to compensate for the tendency to underestimate the actual cost of a first-of-a-kind technology [59].

Appendix F: Overview of openly-available, highly transparent, and detailed techno-economic studies for each industrial sector

To ensure high-quality techno-economic evaluations, a strong level of detailed technical and cost knowledge of the industrial plant without CO_2 capture and with the reference CO_2 capture technology is required. Developing such detailed basis can, in practice, be challenging as industrial sectors are very different from one another and that, even within an industrial sector, industrial plants can differ significantly from one to the another.

Several efforts to develop such detailed studies have been undertaken over the past decades. Furthermore, these studies have also performed detailed evaluation of reference industrial plants and reference CO_2 capture technologies which can be used as base case in comparative assessment. The following subsections provide an overview and discuss openly-available, highly transparent and detailed techno-economic studies[25] for each industrial sector. *To maximise potential further use of this benchmark basis review, the key characteristics, assumptions, and results of each study are summarised in the [Supplementary Information]* of Roussanaly et al. [4] for all sectors. As CO_2 transport and storage costs are very case-specific, as illustrated in section 2.3.3, the CO_2 avoidance cost ($€/t_{CO2,avoided}$) presented in each section below exclude CO_2 transport and storage although the supplementation information includes both CO_2 avoidance cost without and with CO_2 transport and storage when available in the corresponding study.

Overall, while several detailed studies exist on CCS from industrial sectors, it is worth noting that a significant number of these studies have been published by IEAGHG or H2020 EU projects. Most of the key sectors include at least one detailed study apart from the petrochemical, waste-to-energy, and the offshore oil and gas sectors for which only semi-detailed techno-economic studies are available in literature. Finally, it is worth noting that most of these studies are for European locations, often Netherlands, and would need to be adapted for other continents/countries. As such additional studies representing more regional specificity (technology, cost, raw material specificity, local utilities conditions…) would be beneficial to the CCS from industry community.

F.1 Iron and steel mill

In practice, one detailed techno-economic study of blast furnace based-steelmaking plant with and without reference post-combustion MEA-based capture has been published by IEAGHG [78]. The reference plant considered was based on a new build integrated steel mill located in the coastal region of Western Europe producing 4 Mt/y of hot-rolled coil (HRC). While the steel mill consists of 12 major processes and various auxiliaries, nearly 90% of the plant's CO_2 emissions comes from five units: hot stoves, power plant, sinter plant, coke ovens' underfired heaters and lime kilns.

The IEAGHG study established two benchmarked points for CO_2 capture from an iron and steel plant. The first one, referred as Case 2A case, investigated MEA-based CO_2 capture from the flue gases of the hot stoves and the steam generation plant. The second one, Case 2B case, investigated MEA-based CO_2 capture from the flue gases of the underfire heaters of the coke oven batteries, hot stoves, lime kiln, and steam generation. These scenarios result in a reduction of 50 and 60% of the overall plant emissions. Compared to the reference levelised cost of HRC for the plant without capture (429 $€_{2010}/t_{HRC}$), the cases with capture resulted in costs of 487 and 506 $€_{2010}/t_{HRC}$ respectively. Based on this increase and the avoided CO_2 emissions, a CO_2 avoidance cost of 55 $€_{2010}/tCO_{2,avoided}$ was estimated for the case 2A, which achieve 50% avoided CO_2 emissions from

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[25] Transparent studies are defined as reports providing in-depth level of details of the technical and cost assessments of both the industrial plant with and without mature CO_2 capture technology. Journal papers are thus excluded from this screening.

the plant, and 60.6 €$_{2010}$/tCO$_{2,avoided}$ for the case 2B which achieve achieving 60% avoided CO$_2$ emissions from the plant.

F.2 Cement

In the past years, a strong focus has been set on reducing CO$_2$ emissions from cement and, as such, several detailed techno-economic studies of cement with and without reference post-combustion MEA-based CO$_2$ capture has been published by IEAGHG [79] and CEMCAP [222] umbrellas. In both cases, the cement plants considered correspond to the ECRA base cement plant producing with a clinker capacity of 3,000 t/d. However, there are a few differences between both studies. To account for air leakage which periodically appears in cement plant and which are only fixed every once or twice a year, the CEMCAP project included two periods used for design and cost evaluations[26]. Another key difference between both studies is the decision of how to produce the steam required to regenerate the absorbed CO$_2$. While waste heat is recovered to supply around 7% of the heat need in both cases, the IEAGHG study considered a coal-based CHP plant or a NGCC to supply the remaining heat requirement, while CEMCAP assumed a natural gas boiler as well as different alternative strategies. While all these strategies can be valid decisions, these differences might have an impact on the cost. For example, an NGCC case that assumes the excess electricity could be sold at 80 €$_{2014}$/MWh[27] results in a low cost of steam as it gets indirectly subsidized by the high profit on the electricity sale. Thus, the strategies and assumptions in the IEAGHG study resulted on a CO$_2$ avoidance cost of 52.4 €$_{2013}$/tCO$_{2,avoided}$ for the NGCC case and 102.9 €$_{2013}$/tCO$_{2,avoided}$ for the CHP case. Meanwhile, CEMCAP assumptions resulted in a CO$_2$ avoidance cost of 80.2 €$_{2014}$/tCO$_{2,avoided}$ when considering steam production based on a natural gas boiler.

F.3 Refinery

Refineries are the third contributor to industrial emissions. However, CCS from refineries can be challenging to assess due to heterogeneity of refineries, needs to retrofit in a space constraint plant, and the high number of CO$_2$ emissions point sources. The ReCAP study [93] is the only extensive study published on the techno-economic performances of implementing CCS from a refinery. This study evaluated the design, integrations, and techno-economic performances of retrofitting CO$_2$ capture into four different generic refineries: 1) a simple refinery with a nominal capacity of 100 000 bbl/d 2) a medium complexity refinery with a nominal capacity of 220 000 bbl/d 3) a highly complex refinery with nominal capacity of 220 000 bbl/d 4) a highly complex refinery with a nominal capacity of 350 000 bbl/d. Furthermore, as refineries are characterized by the large number of stacks with flue gases of varying CO$_2$ concentration and sulphur content, multiple cases were considered for each refinery scenario. The results of the cost evaluation of the 16 CO$_2$ capture cases resulted in costs of retrofitting CO$_2$ capture with an MEA-based process lies between 145.5 and 189.4 €$_{2015Q4}$/tCO$_2$,avoided. These estimates are significantly larger than estimates available in the literature on CO$_2$ capture for other sources (natural gas and coal power generation, cement, steel, etc.) for three main reasons: 1) the inclusion of the retrofit costs such as interconnection costs 2) the utilities cost is based on the installation of an additional CHP plant, cooling water towers and wastewater plant which are all designed with significant spare capacity in some cases (up to 30% overdesign). 3) Most of the CO$_2$ capture cases considered include small to medium CO$_2$ emission point sources and in some cases low to medium flue gas CO$_2$ content and/or significant amount of sulphur.

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[26]The two time periods were (1) a low air leak time period in which the flue gas contain 22%vol of CO$_2$ and lasting 6 months every year (2) a high air leak time period in which the flue gas contain 18%vol of CO$_2$ and lasting 6 months every year. This aspect is meant to more accurately represent the conditions of a cement plant, but results in higher CAPEX and OPEX compared to an evaluation considering only a low or an average air leak scenario.

[27] Average electricity price in the European Union area was 58.1 €/MWh in 2014

F.4 Hydrogen

While auto-thermal reforming is key to large-scale production of hydrogen, steam methane reforming is the leading technology for production of hydrogen from natural gas and light gas. A detailed techno-economic study of SMR-based hydrogen production plant with and without CCS has been published by IEAGHG [86]. This study evaluated the design, performances, and cost of a new build hydrogen production plant located in the Netherlands producing 100 000 Nm^3/h of hydrogen using natural gas as a feedstock.

In such a plant, the CO_2 can be captured at three different locations: 1) synthesis gas before the H_2 Pressure Swing Adsorption (PSA) 2) tail gas after H_2 PSA 3) flue gas of the SMR furnace. While the two first low locations tend to result in lower cost due to the high CO_2 partial pressure, a main drawback of CCS from these two locations is that only 60 %, approximately, of the plant CO_2 emissions can be captured. On the other hand, CCS from the SMR furnace can reduce the emissions of the hydrogen plant beyond 90%, although the capture cost could be higher than in the other two options.

Based on the considered plant, the IEAGHG study established three benchmark points for CO_2 capture based on chemical absorption: 1) CO_2 capture from shifted syngas using MDEA 2) CO_2 capture from PSA tail gas using MDEA 3) CO_2 capture from flue gas using MEA. These scenarios result in a reduction of 54, 52, and 89% of the overall plant emissions. Compared to the reference levelised cost of hydrogen without capture (11.4 c€$_{2014Q4}$/Nm^3_{H2}), the cases with capture resulted in costs of 13.5, 14.2, and 16.5 c€$_{2014Q4}$/Nm^3_{H2} respectively. Based on these LCOH increases and the avoided CO_2 emissions, CO_2 capture costs of 36.4 and 55.5 €$_{2014Q4}$/$tCO_{2,avoided}$ were estimated for first two cases, and 58.7 €$_{2014Q4}$/$tCO_{2,avoided}$ for the third case which is the only one enabling low-carbon footprint hydrogen.

F.5 Ammonia/ urea and methanol

Currently, 60% of hydrogen syngas produced are used for production of ammonia/urea and methanol. Building on its hydrogen study, IEAGHG published a study on ammonia/urea and methanol production with CCS [83]. This study investigated the performances and cost of a new built plant producing ammonia/urea or methanol without and with CCS. In both cases, the industrial complex was based on the integration of a syngas plant based on SMR from natural gas. In the first case, the syngas plant was integrated in an ammonia plant with a 1350 t/d nominal capacity. Around 95% of the produced ammonia was considered to be further converted downstream in an ammonia plant (2260 t/d) using CO_2 captured from the syngas plant. In the second case, the syngas plant was integrated in a methanol plant with a nominal capacity of 5000 t/d. It is important to note that in both cases, most of the carbon entering the processes end up in the final products: 69.3% in the ammonia/urea case and 79.3% in the methanol case. The cases with CO_2 capture thus aim at capturing around 90% of the remaining CO_2 emissions through post-combustion MEA-based CO_2 capture from the SMR flue gas.

For the ammonia/urea plant, the levelised cost of urea increases from 257.3 to 280.3 €$_{2014Q4}$/t once CCS is implemented. Based on the specific emissions reduction, the corresponding cost of CO_2 capture is 75 or 83.9 €$_{2014Q4}$/$tCO_{2,avoided}$ depending on assumed electricity source (natural gas or a coal power plant). It is worth noting that in the case with capture, part of the CO_2 captured is used to reach a total urea production of 2380 t/d.

For the methanol plant, the levelised cost of methanol increase from 275.1 to 298.9 €$_{2014Q4}$/t by implementing CCS. The obtained costs of CO_2 resulting of thus 70.6 and 78.9 €$_{2014Q4}$/$tCO_{2,avoided}$ depending on the electricity source (natural gas or a coal power plant), thus slightly lower than in the urea case.

One important aspect to note is that as most of the carbon entering the processes end up in the final products and might be released to the atmosphere through the product (or one of its derivates) use [223, 224], the climate impact of the end product might only be moderately reduced through the implementation of CCS in this case.

F.6 Pulp and board

Although a large proportion of these is biogenic emissions, the pulp and board production sector contributes to nearly 5% of the CO_2 emissions of the industrial sector. Furthermore, reducing these emissions is key in achieving the climate ambitions of certain countries as nearly 75% of the pulp and paper production is concentrated in ten countries. A detailed techno-economic study on retrofitting CCS on pulp and board mills was published by IEAGHG [82]. This study assessed two hypothetical reference mills situated in the west coast of Finland. The first one is a pulp mill producing 800,000 air-dried tonne (adt) per year of bleached softwood pulp (BSP). The second one is an integrated pulp and board mill which produces 400,000 adt of board per year and 740,000 adt/y of BSP. For both plants, the main sources responsible for the CO_2 emissions of the plant are the recovery boiler (REC), the multi-fuel boiler (MFB), and the lime kiln (LK). These three sources are responsible for respectively 76, 14, and 10% of the plant non-biogenic emissions. However, it is worth noting that each of these sources also emits 24 tonnes of biogenic CO_2 emissions per tonne of non-biogenic CO_2 emissions. For each plant, retrofitting an MEA-based post-combustion capture from these sources was evaluated on a stand-alone or combined basis thus resulting in six capture scenarios: 1) REC only 2) MFB only 3) LK only 4) REC + MFB 5) REC + LK 6) REC + MFB + LK.

While the cost of the pulp and board plants without capture results in a levelised cost of pulp of 522.6 €2015/adt, this cost varies between 543 and 676 €2015/adt for the pulp mill and 545 and 714 €2015/adt for the pulp and board mill depending on the capture case considered. This results in CO_2 capture cost[28] varying from 52 to 81 €2015/tCO2,avoided for the pulp mill and 72 and 82 €2015/tCO2,avoided for the pulp and board mill. In general, the scenarios based on CO_2 capture from the REC stand-alone or combined with other sources results in the lowest cost. It is worth noting that despite the retrofit cost and the shorter operation duration for the CO_2 capture facility (15 years), the CO_2 capture cost remains rather low as excess steam produced by the mill is assumed to supply the required heat demand for CO_2 regeneration.

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[28] Biogenic and non-biogenic emissions are here considered alike.

Appendix G: Other methods for calculating CO_2 avoidance cost and their associated assumptions

The "net present value" and "annualisation" methods for calculation of CAC are presented in Equation 11 [225] and Equation 12 [226], while a summary of assumptions required to ensure the validity of each CO_2 avoidance cost calculation methods is presented in Table G-1. More details on the links between the different calculation methods and the associated assumptions can be found in Roussanaly [99].

$$CAC = \frac{NPV_{CCS}}{\sum_i \frac{\dot{M}_{CO2,avoided,i}}{(1+r)^i}} \qquad \text{(Eq. G-1)}$$

Where:

- NPV_{CCS} is the net present value of total annual CCS costs (which may vary from year to year).
- $\dot{M}_{CO2,avoided,i}$ is the mass of CO_2 avoided by CCS implementation in year i.
- r is the discount rate.

$$CAC = \frac{I_{CCS,a} + O_{CCS}}{\dot{M}_{CO2,avoided}} \qquad \text{(Eq. G-2)}$$

Where:

- $I_{CCS,a}$ is the annualised investment cost of CCS.
- O_{CCS} is the annual operating cost of CCS.
- $\dot{M}_{CO2,avoided}$ is the annual reduction in CO_2 emissions due to CCS for a plant producing the same amount of product(s) with and without CCS.

Table G-1. Summary of assumptions required to ensure the validity of each CO_2 avoidance cost calculation methods. For the "exhaustive" method none of these assumptions are required [99]

Assumption	"Exhaustive" method	"Net present value" method	"Annualisation" method
Production of industrial plant not affected by CCS implementation	-	Yes	Yes
Additional costs and CO_2 emissions avoided due to CCS implementation can be assessed separately	-	Yes	Yes
Annual operating costs and CO_2 emissions avoided are constant over project duration	-	-	Yes
CO_2 emissions linked to construction of the CCS facility can be neglected or excluded	-	-	Yes

Appendix H: Definitions of Technology Readiness Levels

Table H-1. Definitions of TRL by different institutes

TRL	European Commission, Horizon2020 [227]	UK government [228]	NASA [229]	EPRI [142]	IEA [230]
1	Basic principles observed	Basic principles established	Basic principles observed and reported	Basic principles, observed, initial concept	Initial Idea: basic principles have been defined
2	Technology concept formulated	Invention and Research	Technology concept and/or application formulated	Formulation of the application	Application formulated: concept and application of solution have been formulated
3	Experimental proof of concept	Proof of concept	Analytical and experimental critical function and/or characteristic proof of concept	Proof of concept, tests, component level	Concept needs validation: Solution needs to be prototyped and applied
4	Technology validated in the lab	Bench scale	Component and/or breadboard validation in laboratory environment	System validation in a laboratory environment	Early prototype: prototype proven in test conditions
5	Technology validated in relevant environment	Pilot scale	Component and/or breadboard validation in relevant environment	Sub-system validation in a relevant environment	Large prototype: Components proven in conditions to be deployed
6	Technology demonstrated in relevant environment	Large scale	System/subsystem model or prototype demonstration in a relevant environment	Fully integrated pilot tested in a relevant environment	Full prototype at scale: prototype proven at scale in conditions to be deployed
7	System prototype demonstration in operational environment	Inactive commissioning	System prototype demonstration in a space environment	Sub-scale demonstration, fully functional prototype	Pre-commercial demonstration: solution working in expected conditions
8	System complete and qualified	Active commissioning	Actual system completed and "flight qualified" through test and demonstration	Commercial demonstration, full scale deployment in final form	First-of-a-kind commercial: commercial demonstration, full scale deployment in final form
9	Actual system proven in operational environment	Operation	Actual system "flight proven" through successful mission operations	Normal commercial service	Commercial operation in relevant environment: solution is commercially available, needs evolutionary improvement to stay competitive
10					Integration at scale: solution is commercial and competitive but needs further integration efforts
11					Proof of stability: predictable growth

Appendix I: Mathematical representations of uncertainty analysis

In OAT sensitivity analysis, the model output vector $\mathbf{y}$ is only evaluated against a minimum and maximum value of an input parameter x_i. It assumes a base case vector of input parameters $\mathbf{x^0}$ and a sensitivity perturbation (min/max, the plus/minus 10%) of the input parameters $\mathbf{x^+}$. The difference between the base case and the sensitivity case is then $\Delta^+ \mathbf{x} = \mathbf{x^+} - \mathbf{x^0}$ Δ^+. The output of the sensitivity analysis is the delta between $y_i{}^+$ and $y_i{}^{+0}$:

$$\Delta_i^+ y = g(x_i + \Delta x_i^+, \mathbf{x}^0_{\sim i}) - g(\mathbf{x}^0) \qquad \text{(Eq. I} - 1)$$

Where $\mathbf{x}^0_{\sim i}$ is the vector of all inputs other than i (i.e., the inputs that are kept constant). A one-way sensitivity function $h_i(x_i)$ can be defined as:

$$h_i(x_i) = g(x_i;\ \boldsymbol{x}^0_{\sim i}) \qquad \text{(Eq. I} - 2)$$

A typical representation of one-way sensitivity analysis is by so-called spider-plots, where the sensitivity of the output values is plotted against changes in the vector of input values. To plot the changes to all input parameters in one graph, they need to be normalised (calculated as a percentage deviation) according to the function:

$$h_i^*(x_i) = h_i(x_i) - g(\boldsymbol{x}^o) = g(x_i;\ \boldsymbol{x}^0_{\sim i}) - g(\boldsymbol{x}^o) \qquad \text{(Eq. I} - 3)$$

Appendix J: Guideline for the characterisation of probability density functions by Hawer et al. [180]
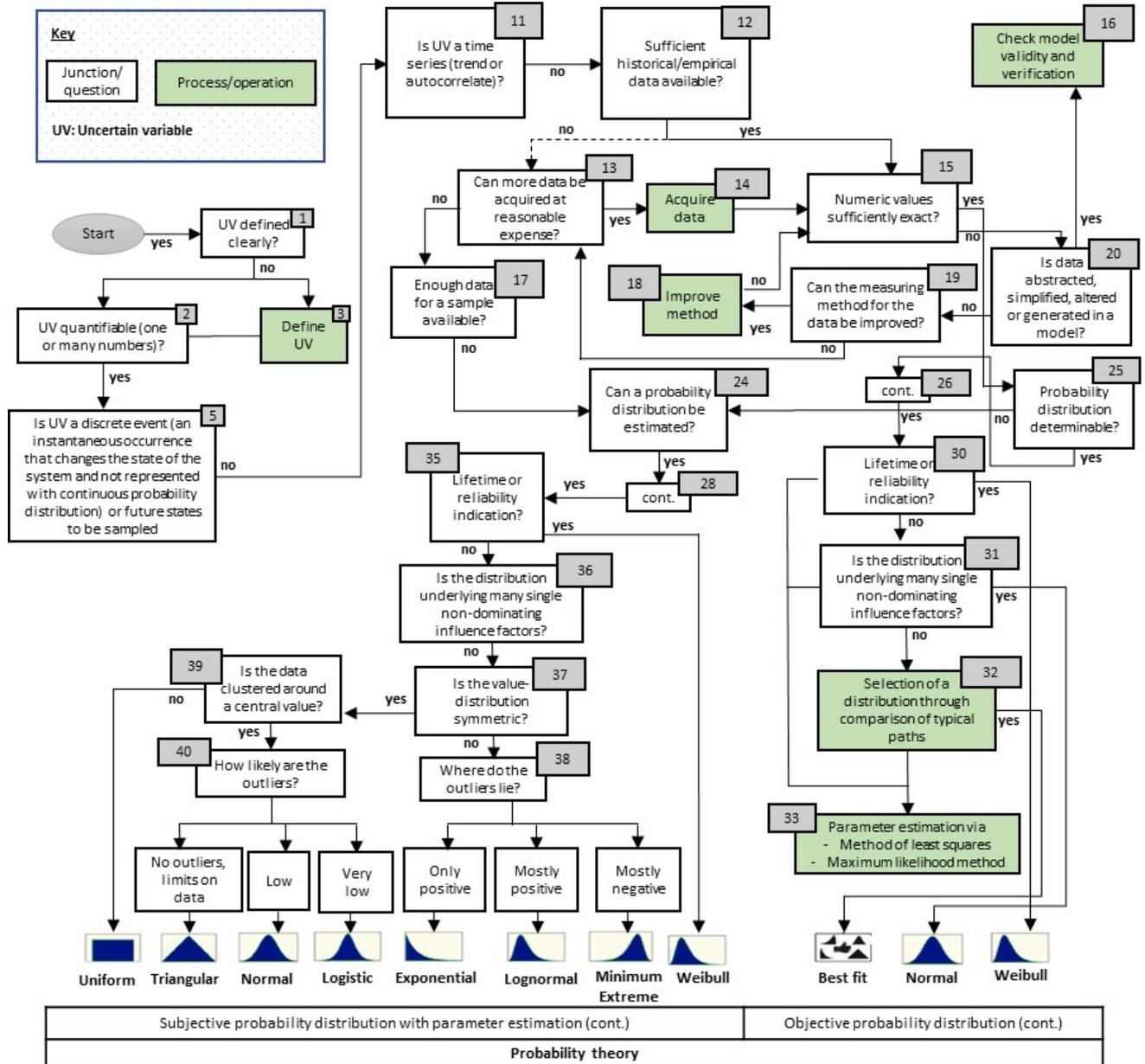

Figure J-1. Guideline for the classification and quantification of uncertainty, based on Hawer et al. [37]. UV is short for Uncertain Variable; the numbers in the boxes refer to the original numbering by Hawer et al [37], of which we used a subset.

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