

Decision support for ranking Pareto optimal process designs under uncertain market conditions.

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Abstract

Considering the uncertainty of economic conditions, multi-objective optimisation can be favoured to single-objective optimisation for process design. However, from the Pareto sets generated by multi-objective optimisation it is not obvious to identify the best one, given that each solution is optimal with regard to the selected objectives. A method taking into account the economic parameters uncertainty to support decision making based on the Pareto-optimal solutions is proposed. It uses a Monte-Carlo simulation to define the probability of each of the Pareto optimal configuration to be in the list of the best configurations from the economical point of view. For a given economic context defined the most probable best configurations are identified. The proposed method is applied to two cases: the CO₂ capture in power plants and synthetic natural gas production from biomass resources. The results allow to identify the most attractive system designs and give recommendations for the process engineers.

Keywords: Decision making, Economic conditions, Multi-objective

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Nomenclature

Abbreviations

ATR Autothermal Reforming

BM Biomass

CC Carbon Capture

CCS Carbon Capture and Storage

CFB Circulating Fluidised Bed

CFBO₂ Circulating Fluidised Bed directly heated with O₂

CGCL Cold Gas Cleaning

CPI Current Policy Initiatives

DH District Heating

ETS Emission Trading System

FICFB Fast Internally Circulating Fluidised Bed

pFICFB Pressurised Fast Internally Circulating Fluidised Bed

GWP Global Warming Potential

HGCL Hot Gas Cleaning

IPCC International Panel on Climate Change

LCA Life Cycle Assessment

MEA Monoethanolamine

NG Natural Gas

NGCC Natural Gas Combined Cycle

PSA Pressure Swing Adsorption

SNG Synthetic Natural Gas

WGS Water Gas Shift

Greek letters

Δh^o Lower heating value, kJ/kg

ϵ Energy efficiency, %

Roman letters

COE Electricity production cost, \$/GJ_e

\dot{E} Mechanical/electrical power, kW_e

\dot{m} Mass flowrate, kg/s

\dot{n} Molar flowrate, kmol/s

\dot{Q} Heat Flow, kW

1. Introduction

To meet the CO₂ reduction targets and to ensure a reliable energy supply, the development and wide scale deployment of cost-competitive innovative low-carbon energy technologies is necessary. Carbon capture and storage (CCS) in power plants and the use of renewable resources for the poly-generation of biofuels, heat and power are considered as promising measures. The thermodynamic performance of different process designs depends on the process configuration (i.e. technological options and operating conditions) while the market competitiveness depends in addition on the economic conditions, especially on the resource price. Therefore, it is important to evaluate and optimise the process designs with regard to multiple competing objectives such as efficiency, investment cost and environmental impacts. Since there is a trade-off between the objectives and that the economic performance is highly influenced by the market conditions, it is difficult to identify the

best process design from multi-objective optimisation results by taking into account the economic parameters uncertainty.

The influence of the economic conditions is frequently investigated in literature based on extreme scenarios, *as in [1] for the European market and in [2] for the global market*, or on sensitivity analysis. A method to support decision making based on multi-criteria decision analysis taking into account uncertainties is developed by [3]. In [4] a method for decision support in chemical process design based on the navigation on Pareto sets is proposed. *The innovative slider concept [5] used to navigate on the Pareto frontiers supports decision making by choosing the best compromise between conflicting objectives.* This method does not account for parameters uncertainties. Multiple decision making methods have been developed for management activities. *However, the applications for process system designs are limited. To assist the multi-objective decision analysis an incentive model for primary energy savings and carbon dioxide emission reduction is presented in [6] to evaluate the Pareto operation decisions derived from a stochastic model including uncertainties. In [7] decision making and robustness strategies are combined with multi-objective optimization to optimize polymer extrusion processes.*

So far systematic approaches taking into account the economic conditions fluctuation for the decision making based on the optimisation results are rarely applied and process integration aspects and life cycle assessment are not systematically assessed. Based on the systematic optimisation approach previously presented [8] and [9], a method, taking into account the economic parameter sensitivity, to support decision making based on the Pareto-optimal solutions is proposed here. The influence of the economic

scenario on the decision-making is studied by taking into account the sensitivity of the economic performance to the carbon tax, the resource prices, the operating time, the investment and the interest rate.

1.1. Uncertain market conditions

The analysis of the fossil fuel market over the last years, reveals diverse patterns over time and with regard to the geographic location (i.e. Europe, the United States and Japan). This is revealed by the the energy statistics [10] and the oil and gas market data reported by the IEA [11], as well as the publications of the European Commission reporting trends [12], raw data [13] and future scenarios [14]. The large fluctuations result from multiple factors affecting the trading. *In the past, the natural gas price evolution went in pair with the oil price. However, with the exploitation of shale gas this pattern changes.* The coal price which is less affected by the oil price and is predicted to stabilise around $5\$/GJ_{coal}$ in 2030 [14]. Consequently, the gas to coal price ratio is projected to increase steadily and will together with the carbon price influence investment decisions in the power sector. European gas prices are about twice as high as US gas prices and are projected to be $10\$/GJ_{NG}$ in 2020, $12\$/GJ_{NG}$ in 2030 and $16\$/GJ_{NG}$ in 2050 for the *EU 'Reference'* energy scenario [14]. In a similar way, the carbon tax price is influenced by multiple factors. The emission trading system (ETS) directive has been established in the European Union to promote greenhouse gas emissions reductions in a cost effective and economically efficient manner [15]. The carbon price drop from around $25\€/t_{CO_2}$ in 2008 to below $10\€/t_{CO_2}$ in the second half of 2011 because of the surplus of allowances and international credits and the financial crisis. According to the predictions from the Energy Roadmap

2050 [14], carbon tax prices will rise moderately until 2030 and then significantly to provide support to low carbon technologies and energy efficiency. For the current policy initiatives (CPI) scenario, taking into account the latest policies on energy efficiency, taxation and infrastructure, the carbon tax is predicted to increase to 15€/t_{CO2} in 2020, to 32€/t_{CO2} in 2030 and to 51€/t_{CO2} in 2050. Comparing the costs projections for different energy and policy scenarios a large variation of the predictions is found. This highlights the large uncertainty of costs projections and the need to account for different economic scenarios when evaluating the competitiveness of processes to support investment decisions.

2. Methodology

The applied thermo-environomic modelling and optimisation approach illustrated in Figure 1 combines flowsheeting and energy integration techniques with economic evaluation and life cycle assessment (LCA) [8] in a multi-objective optimisation framework previously presented in [16] and [9]. *The main steps are summarized as following:*

1. *Establishment of the process superstructure and development of the process models.*
2. *Computation of the energy integration.*
3. *Assessment of the performance indicators.*
4. *Multi-objective optimisation.*
5. *Decision making.*

After the assessment of candidate process technologies in a superstructure, energy-flow models are established with conventional flowsheeting soft-

ware computing the chemical and physical transformations and the associated heat transfer requirements of each process option. The heat recovery and the combined heat and power production is optimised in the energy integration model by using the heat cascade constraints and a linear programming model minimising the operating cost [17]. The process needs are satisfied by different utilities including waste and process gas combustion, Rankine cycle, gas turbine and cogeneration. To evaluate the economic performance, the equipments are first sized and the costs are then evaluated by applying the approach and correlations reported in [18] and [19]. A multi-objective optimisation based on an evolutionary algorithm [20] is finally performed to assess the trade-offs between competing objectives and identify optimal process designs and operating conditions. Evolutionary algorithms working with populations instead of a single data point, generate multiple promising solutions in the form of a Pareto-optimal frontier. The Pareto-optimal solutions correspond to the configurations for which it is not possible to improve one objective without simultaneously downgrading one of the other objectives. It is a priori not obvious which configuration has to be chosen from the Pareto results.

Therefore, the aim is here to propose an approach which allows to identify the optimal process design from the Pareto-optimal solutions taking into account the economic conditions sensitivity.

2.1. Decision support approach

In this approach (Figure 1), the economic conditions fluctuation is first described by probability distribution functions (Section 2.1.1). By applying the distribution functions a series of 1000 economic scenarios is randomly

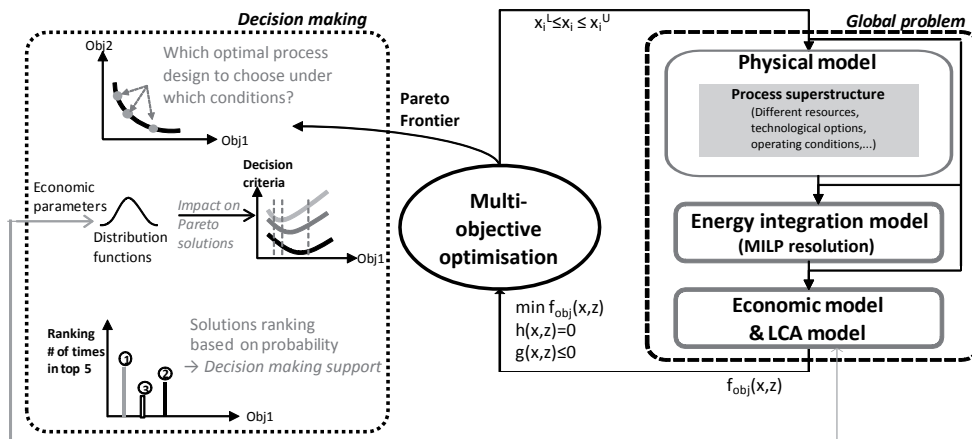


Figure 1: Thermo-environmental optimisation strategy to support decision-making.

generated. For every single economic scenario and for each configuration (i.e. process design) of the Pareto frontiers resulting from the multi-objective optimisation, the decision criterion/criteria is/are then recomputed. From the Pareto-optimal solutions the designs that yield the best performance (best, top 5 and top 10) with regard to the decision criteria are then identified for each economic scenario. After having identified the most economically competitive designs in the wide range of economic scenarios, it can be found out if some configurations are dominating or if some are never part of the best performing ones. To evaluate this quantitatively, the probability to be part of the best performing designs is assessed for each point of the Pareto front. The different process designs can then be ranked based on this probability. This allows finally to identify the most economically competitive process design in a wide range of economic scenarios.

The following steps summarise the decision support approach that allows to rank the different process designs and to identify the best process design

taking into account the economic parameters sensitivity.

1. Generation of the Pareto frontiers by multi-objective optimisation. When several technology options can be considered, one Pareto frontier is generated per process option.
2. Definition of probability distribution functions for each uncertain economic parameter (i.e. resource price, carbon tax, interest rate,...).
3. Generation of a set of 1000 different economic scenarios based on the probability distribution functions.
4. For each economic scenario:
 - Recalculation of the decision criteria (i.e. lowest production costs, highest profit, ...) for each Pareto optimal solution.
 - Ranking of the process designs with regard to the decision criterion.
 - Identification of the best and top 5 process designs.
5. Repeat step 3 for each economic scenario.
6. *Assessment of the probability to perform the best. For each Pareto optimal solution the probability to be the best and the probability to be part of the 5 best process configurations are calculated. The best performance is evaluated based on one or several decision criteria/on, being a chosen performance indicator (i.e. operating cost, profitability, ...).*
7. Identification of the overall best, most robust process design.

2.1.1. Distribution functions - Uncertain parameters

The economic conditions fluctuation is described by probability distribution functions. Characteristic distribution functions that are applied here are the normal, uniform and beta distributions. Different approaches are discussed in [21]. The normal or Gaussian distribution is a continuous probability distribution that has a bell-shape probability density function given by Eq.1. The parameter μ is the mean and σ^2 is the variance and σ the standard deviation. The continuous uniform distribution is characterised by the lower a and upper b endpoint defining the distribution support. Each point in this interval is equally probable. The probability density function for $x \in [a, b]$ is given by Eq.2. The beta distribution is a continuous probability distribution that is defined in the interval $[0,1]$ and is parameterised by two positive shape parameters a and b . This distribution characterised by the probability density function Eq.3 is frequently applied to model the behaviour of random variables limited to a finite interval.

$$f(x; \mu, \sigma^2) = \frac{1}{\sigma\sqrt{2\Pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \quad (1)$$

$$f(x) = \frac{1}{a-b} \quad (2)$$

$$f(x; a, b) = c \cdot x^{a-1} \cdot (1-x)^{b-1} \quad (3)$$

Based on available literature data about economic scenarios projections from IEA and the European Commission [10, 11, 14, 12, 13, 1], the lower and upper boundary values are defined for each economic parameter. The appropriate distribution function is then selected and the characteristic parameters are identified in such a way that boundary values are part of the distribution.

The distributions for the natural gas price and the carbon tax are represented in Figure 2 and the parameters of the probability density functions are reported in Table 1. *The variation of the natural gas price is represented by a normal distribution. The carbon tax price which is assumed to increase most probably in the future is described by a beta distribution function.*

Table 1: Definition of the parameters of the distribution functions for the natural gas price and carbon tax. *The boundary values are based on [10, 11, 14, 12, 13, 1]*

	Scenario			Distribution functions parameters			
	Base	Low	High	Distribution	Param. A	Param. B	Param. C
Natural gas price [\$/GJ _{NG}]	9.7	5.5	14.2	Normal	$\mu=9.7$	$\sigma=2.5$	-
Carbon tax [\$/t _{CO2}]	35	20	55	Beta	a=2	b=1.5	c=100

3. Applications

The previously described methodology is applied to identify under uncertain market conditions the best process designs from the multi-objective optimisation results of two different systems: a) CO₂ capture in power plants and b) Synthetic natural gas (SNG), heat and power poly-generation from lignocellulosic biomass.

3.1. CO₂ capture in power plants

For CO₂ capture in power plants three major concepts are suitable: post-, pre- and oxyfuel-combustion. The thermo-economic competitiveness of these CO₂ capture options depends on the power plant layout, the resources type, the capture technology and the economic conditions. *The penalty of CO₂ capture in terms of efficiency and costs has been evaluated by the European*

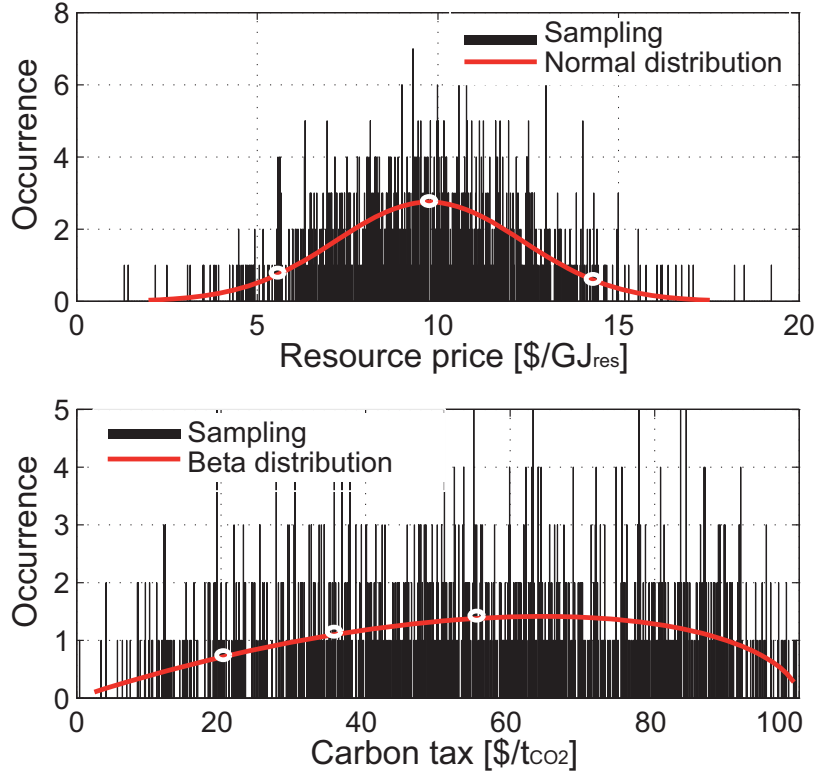


Figure 2: Distribution function (in red) of the natural gas price (top) and of the carbon tax (bottom). The white dots correspond the values reported in Table 1. The black bars represent the random sample of 1000 values.

Technology Platform [1], the International Panel on Climate Change [22] and the International Energy Agency [2]. Diverse layouts have been compared by [23] and [24]. Different process configurations based on fossil and renewable resources have been evaluated based on process modelling and simulation in [25–27] and [28] without including detailed process integration and economic considerations. An extensive life cycle assessment (LCA) of CO₂ capture options is performed in [29], while economic and environmental aspects are combined in [30]. Nevertheless, none of these studies combines extensive flow-

sheeting with thermodynamic, economic and environmental considerations simultaneously to make a comprehensive comparison of CO₂ capture options in power plants applications. All these studies reveal that the competitiveness of CO₂ capture processes on the future energy market is determined by the economic conditions, especially the resource price and the introduction of a carbon tax. The influence of the economic conditions is frequently investigated based on extreme scenarios or sensitivity analysis [1, 31], however no systematic approach taking into account the economic conditions fluctuation for the decision making based on the optimisation results is applied.

The decision support approach is applied here to identify the best CO₂ capture process design under uncertain market conditions.

3.1.1. CO₂ capture process description

Three representative CO₂ capture options, *illustrated in Figure 3*, are investigated: 1) Post-combustion CO₂ capture by chemical absorption with monoethanolamine (MEA) applied to a natural gas combined cycle (NGCC) plant (582 MW_{th,NG}). This option, abbreviated hereafter as *NG post-*, is the same as the one described in [32]. 2) Pre-combustion CO₂ capture by physical absorption with Selexol in a natural gas fueled power plant (725 MW_{th,NG}) based on autothermal reforming. This option, referred to hereafter as *NG pre-*, has been described and analysed previously in [33] and [34] for H₂ production applications. 3) Pre-combustion CO₂ capture by physical absorption with Selexol in a biomass fired power plant (380 MW_{th,BM}) based on fast internally circulating fluidised bed gasification. The biomass resource is wood characterised by a weight composition of 51.09%C, 5.75%H, 42.97%O and 0.19% N, and a humidity of 50%wt. This option, labeled hereafter as

BM pre-, has been described and analysed previously in [35]. For all the cases CO₂ compression to 110 bar for subsequent transport and storage is included to evaluate the thermo-environomic performance. *The key operating parameters of the investigated pre- and post-combustion processes are reported in Tables 2 and 3.*

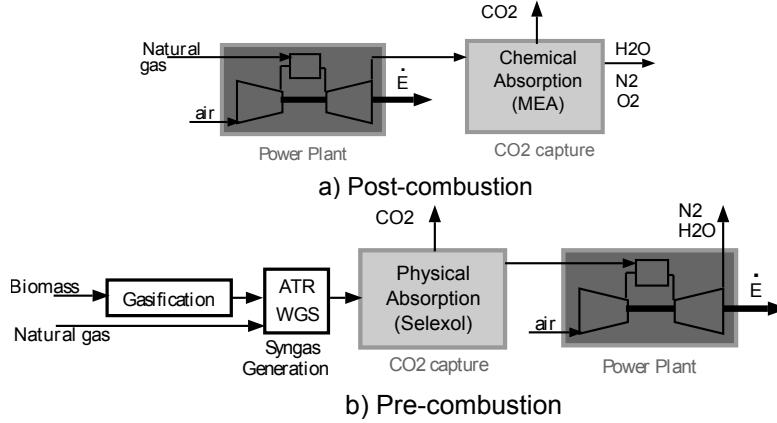


Figure 3: Investigated CO₂ capture processes for electricity production.

A multi-objective optimisation is performed with the objective of maximising the energy efficiency (Eq.4) and the CO₂ capture rate (Eq.5) with regard to the process operating parameters (i.e. reforming, gasification and water gas shift temperature and pressure, steam to carbon ratio, capture unit design, absorption and desorption operating conditions, cogeneration system configuration,... (Tables 2 and 3).

The energy efficiency ϵ_{tot} is defined by the ratio between the net electricity output ($\Delta E^- = \dot{E}^- - \dot{E}^+$) and the resources energy input, expressed on the basis of the lower heating value (Δh^0), according to Eq.4.

$$\epsilon_{tot} = \frac{\Delta E^-}{\Delta h_{NG,in}^0 \cdot \dot{m}_{NG,in}} \quad (4)$$

Table 2: Decision variables for the post-combustion CO₂ capture process using chemical absorption process with monoethanolamine.

Operating parameter	Range
FGR [-]	[0-0.56]
Lean solvent CO ₂ loading [kmol/kmol]	[0.18-0.25]
Rich solvent CO ₂ loading [kmol/kmol]	[0.4-0.5]
Rich solvent pre-heat T [°C]	[95-105]
Rich solvent re-heat T [°C]	[115-125]
LP stripper pressure [bar]	[1.7-2.1]
HP / LP pressure ratio [-]	[1-1.5]
MEA % in solvent [-]	[0.3-0.35]
Absorber steam out [kg _{H2O} /t _{FG}]	[306-309.5]
Split fraction [-]	[0-0.7]
Nb stages absorber	[10-17]
Nb stages HP stripper	[8-15]
Nb stages LP stripper	[6-10]
Absorber diameter [m]	[6-12]
HP stripper diameter [m]	[3-6]
LP stripper diameter [m]	[2-5]

$$\eta_{CO_2} = \frac{\dot{n}_{C_{captured}}}{\dot{n}_{C_{in}}} \cdot 100 \quad (5)$$

To evaluate the economic performance the electricity production costs, including the annual capital investment and the operation and maintenance costs, are computed. *The capital investment of each equipment assessed based on cost correlations reported in [18] and [19] is update to year 2014 with the Marshall and Swift cost index accounting for inflation. The total capital investment is annualised taking into account the interest rate and the plant lifetime. The maintenance costs are assumed to be 5% of the initial annual investment. The operating costs mainly consist of the purchase of the resources, which are here the natural gas and biomass feedstock.*

The competitiveness of the CO₂ capture options is compared with a conventional NGCC plant (559MW_{th,NG}) without CO₂ capture characterized by an efficiency of 58.7%, specific CO₂ emissions of 105kg_{CO2}/GJ_e, COE of

Table 3: Decision variables for the pre-combustion CO₂ capture (physical absorption with Selexol solvent) processes using natural gas or biomass as a feedstock.

Section	Specification	Range
Biomass drying	T [K]	473
Biomass pyrolysis	T [K]	533
Biomass gasification	$\theta_{wood,gasif_in}$ [%wt]	[5-35]
	T [K]	[1000-1200]
	P [bar]	[1-15]
SMR after gasification	T [K]	[950-1200]
ATR	T [K]	[780-1400]
	P [bar]	[1-30]
	S/C [-]	[0.5- 6]
WGS	T _{HTS} (NG/BM) [K]	[523-683]/[573-683]
	T _{LTS} (NG/BM) [K]	[423-523]/[423-573]
	P (BM) [bar]	[1-25]
	S/C (BM) [-]	[0.2-4]
CO ₂ capture	Selexol/CO ₂ ratio [kg/kg]	[8-14]
	Absorber T [$^{\circ}$ C]	[-18-173]
	Absorber P [bar]	[10-60]
	Nb stages absorber	10
	Absorber packing	Pall ring
	Regeneration P [bar]	[1-10]
	Regeneration T [$^{\circ}$ C]	[25-100]

18.3\$/GJ_e without carbon tax.

The multi-objective optimisation results illustrated in Figure 4 reveal the trade-off between the energy efficiency and the CO₂ capture rate. An increase of the CO₂ capture rate leads to a decrease of the energy efficiency due to the energy consumption for CO₂ capture and compression to 110 bar. Considering only these two performance indicators no evident decision in favor of one specific process configuration can be made. To evaluate the process market competitiveness, the economic dimension has to be included. CO₂ capture induces additional investment costs for the capture equipment (i.e. absorber and desorber) and the CO₂ compressor. Together with the

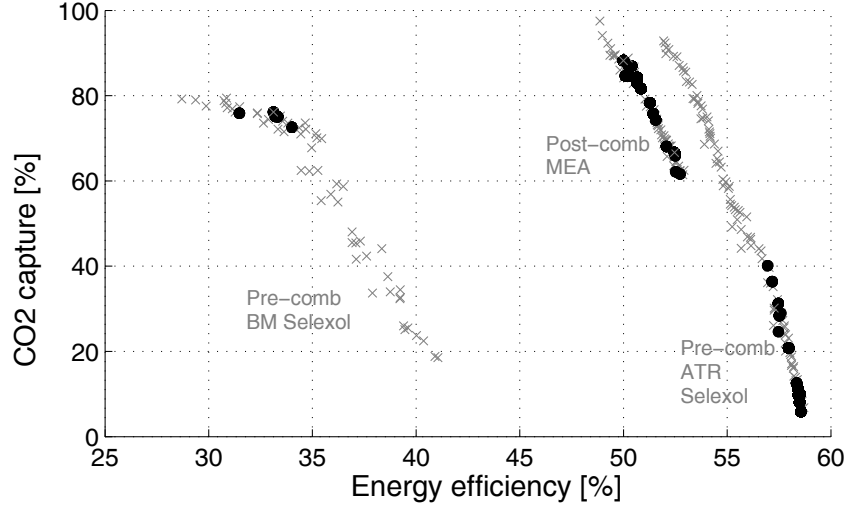


Figure 4: Power plants performance with CO₂ capture: Decision-making based on the Pareto front (black points).

reduced electricity production, this increase of the investment leads to an increase of the electricity production costs. When a carbon tax is introduced the cost penalty of CO₂ capture is reduced by the benefit from the tax compared to a plant without CO₂ capture inducing larger emissions. Consequently, there are break even economic conditions for which CO₂ capture becomes beneficial. *To take into account the economic conditions uncertainty for the decision making, the fluctuation of the different economic parameters is described by the distribution functions following the approach described in Section 2.1.1. The distribution functions are summarized in Table 4. The boundary values used to set up the distribution functions of the resource price and the carbon tax are based on [10, 11, 14, 12, 13, 1]. The yearly operation is characterised by a beta distribution as the as target of the plant is to operate closely to its design value which was here 8600 h/y. Most plants tending*

to operate for more than 10 years and operating likelihood between 20 and 30 years, a beta distribution is used to reflect the variation of the economic lifetime. The interest rate being affected by the market and the trading a normal distribution around the usual rate of 6% is used. For the investment cost estimation a precision of $\pm 30\%$ is reported in [18], which is reflected by the uniform distribution. For ranking the different solutions the chosen decision criteria is the electricity production costs (COE) including a carbon tax.

Table 4: Definition of the economic scenarios and parameters of the distribution functions for the economic assumptions. *The distribution functions are set up based on values from [10, 11, 14, 12, 13, 1]*

	Distribution functions parameters			
	Distribution	Param. A	Param. B	Param. C
Resource price [$\$/GJ_{NG}$]	Normal	$\mu=9.7$	$\sigma=2.5$	-
Carbon tax [$\$/t_{CO_2}$]	Beta	a=2	b=1.5	c=100
Yearly operation [h/y]	Beta	a=3.9	b=1.2	c=8600
Economic lifetime [y]	Beta	a=5.8	b=4	c=40
Interest rate [%]	Normal	$\mu=0.06$	$\sigma=0.01$	-
Investment cost [%]	Uniform	a=-0.3	b=0.3	-

3.1.2. Decision making based on the Pareto-optimal solutions

The variation of the economic performance of the Pareto optimal solutions with the economic conditions is illustrated in Figure 5.

The configurations yielding the best economic performance are identified in Figures 5&4. Figure 4 illustrates by the black dots how the decision-making along the Pareto-optimal frontier changes. Figure 5 reports the variation of the COE of the most economically competitive configurations identified from the Pareto-optimal solutions between the upper and lower

borderline. The economic conditions corresponding to the lower and upper boundary are respectively: 5042/7260h/y operation, 7.29/62.3\$/GJ_{res} resource price, 89/55.8\$/t_{CO2} carbon tax, 6.3/4.1% interest rate, 25.5/20y lifetime and -23/+25% investment costs estimation. For the base case economic scenario biomass fed processes are not competitive and post-combustion CO₂ capture performs best for capture rates around 70-85%. When gas prices increase, the natural gas based processes become uncompetitive compared to the base case biomass configurations. These results point out the competition between the processes and the influence of the economic scenario on the decision-making. This competition is highlighted in Figure 6 evaluating the overall competitiveness of each Pareto-optimal solution compared to the most-economically competitive solution. The post-combustion process configuration capturing 83% of the CO₂ emissions yields a relative competitiveness of 1 since this solution is the most economically competitive one in the large range of economic conditions. These results clearly show the close competition between post- and pre-combustion and underline that the CO₂ capture rate is a key factor defining the economic performance. Pre-combustion CO₂ capture configurations, being slightly more expensive for similar capture rates, yield however slightly better efficiencies. Depending on the production scope, this could affect decision-making for the more expensive solution. For some marginal economic scenarios CO₂ capture in biomass fed power plants becomes a competitive alternative. In fact, the benefit from the carbon tax outweighs the efficiency penalty for capture rates around 70%. The performance results of the most economically competitive process configurations are compared with the conventional NGCC

plant without CO₂ capture and summarised in Table 5. These results show how the most economically competitive process configurations can be identified from the Pareto-optimal solutions by applying the selection approach taking into account the economic conditions fluctuation.

Table 5: Process performance.

System	NGCC no CC	Post-comb MEA	ATR Selexol	BM Selexol
Feed [$MW_{th,NG/BM}$]	559	582	725	380
CO ₂ capture [%]	0	82.98	78.63	69.93
ϵ_{tot} [%]	58.75	50.65	53.59	35.45
Base case economic scenario				
COE no tax [$\$/GJ_e$]	18.31	22.7	23.7	46.1
COE incl. tax [$\$/GJ_e$]	22	23.2	24.5	21.1
Economic scenario variation				
COE incl. tax [$\$/GJ_e$]	18.3-28.8	9-40	12.8-42	15-69
Environmental Performance (FU=1GJ _e)				
CO ₂ emit. [kg_{CO_2}/GJ_e]	105	13.9	22.2	-198.1
IPCC GWP [$kg_{CO_2,eq}/GJ_e$]	120	35.4	42.2	-167

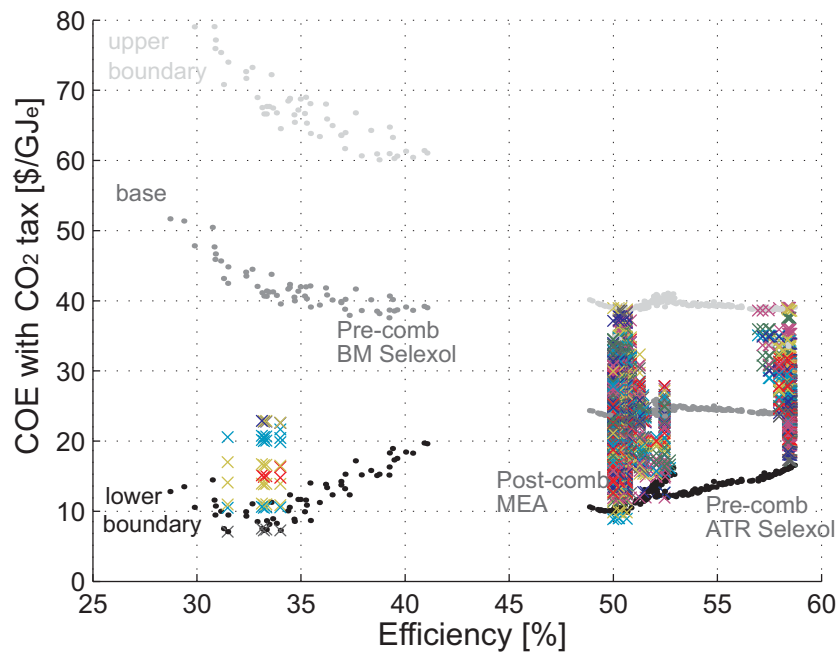
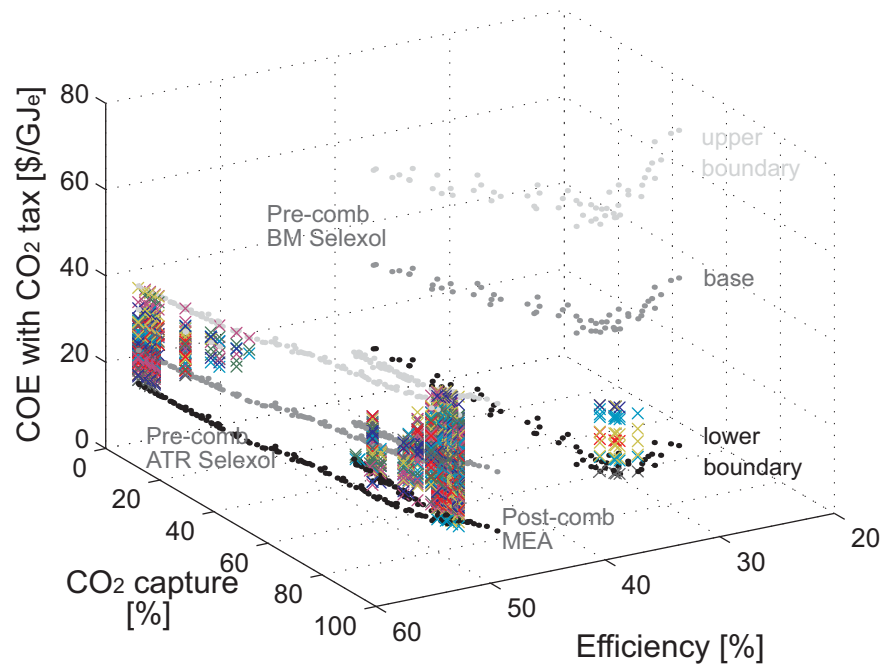


Figure 5: Power plants performance with CO₂ capture: Influence of the economic scenario on the decision-making based on the top 5 configurations yielding the best economic performance. The crosses (x) represent for each economic scenario the 5 selected configurations. Top: 3D-representation, Bottom: 2D-representation

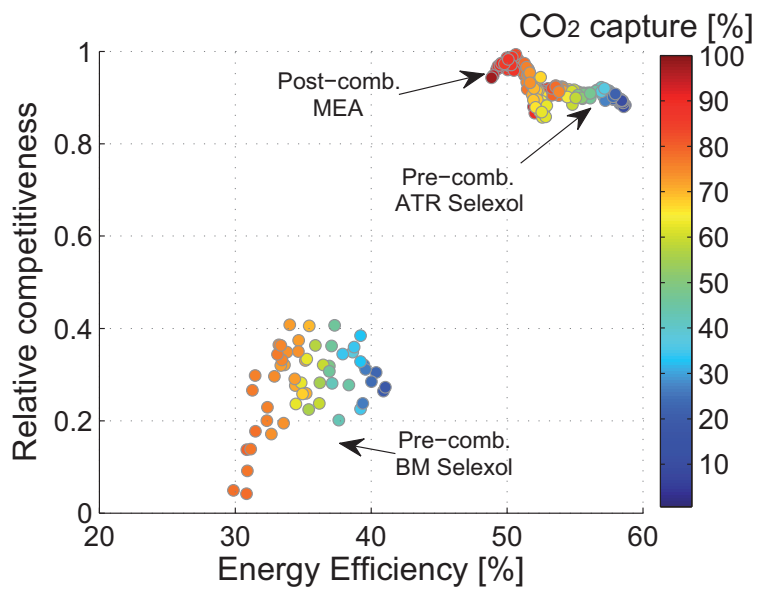


Figure 6: Relative competitiveness.

3.2. SNG production from biomass

The production of synthetic natural gas (SNG) from lignocellulosic biomass was investigated by Gassner et al. [16], based on the same thermo-environmental optimization methodology [8]. The proposed superstructure of the SNG process includes several process options for biomass drying, gasification, cleaning, CO₂ removal and SNG upgrading. In [36] a database of Pareto-optimal flowsheets for all the potential combinations of candidate technologies has been generated by combining the superstructure process model with multi-objective optimisation techniques. *The database consists of 118 Pareto frontiers that differ mainly by the following technology choices (illustrated in Figure 7):*

- *Wood drying technology: drying with hot air or steam*
- *Gasification technology: fast internally circulating fluidised bed (FICFB) gasifier at atmospheric pressure or pressurized (pFICFB) and circulating fluidised bed (CFB) gasification directly heated with O₂ (CFBO₂).*
- *Gas cleaning technology: hot gas cleaning (HCL) or cold gas cleaning (CCL)*
- *Methane upgrading technology (i.e. CO₂ capture): pressure swing adsorption (PSA), Selexol absorption and membrane processes. The upgrading can be performed upstream or downstream the methanation*

The different Pareto frontiers are described in detail and listed in Appendix.

The influence of the economic conditions and of the plant scale were briefly discussed in [36] and the most economically plants have been identified based on the maximum biomass break even cost for different conditions.

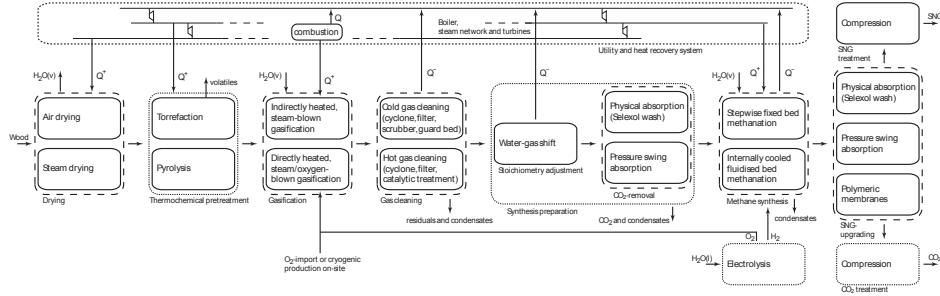


Figure 7: Process superstructure of the SNG production (Figure reproduced from [36]).

Since the different process designs differ in terms of the amount of electricity and heat that is consumed, respectively produced, the economic competitiveness is highly dependent on the market parameters such as the SNG, heat and electricity selling price and the biomass and electricity purchase price. To assess systematically the influence of the economic conditions and to rank the different process designs based on the probability to be part of the top performing ones the decision support approach previously described is applied here.

The analysis is performed for a plant scale of 100MW_{th} . It is considered that the produced SNG is used as an automotive fuel. The produced electricity is sold as 'green' electricity. The economic conditions uncertainty is assessed through the distributions functions reported in Table 6 which have been defined based on data from [37–39]. The considered decision criteria are the SNG production costs, the resources profitability (obtained profit), and the overall ranking with regard to the 2 decision criteria (prod. cost and profitability).

Table 6: Definition of the economic scenarios and parameters of the distribution functions for the economic assumptions.

	Distribution functions parameters			
	Distribution	Param. A	Param. B	Param. C
Biomass price [$\$/\text{MWh}_{BM}$]	Normal	$\mu=28.6$	$\sigma=3.5$	-
\dot{E} price [$\$/\text{MWh}_e$]	Normal	$\mu=145$	$\sigma=15$	-
\dot{E} price (green) [$\$/\text{MWh}_e$]	Normal	$\mu=165$	$\sigma=20$	-
Distributed heat price [$\$/\text{MWh}$]	Beta	$a=5.3$	$b=1.37$	$c=92$
SNG price (automotive fuel) [$\$/\text{MWh}_{SNG}$]	Normal	$\mu=110$	$\sigma=20$	-
Biodiesel price [$\$/\text{MWh}_{FAME}$]	Normal	$\mu=105$	$\sigma=20$	-
Yearly operation [-]	Normal	$\mu=0.9$	$\sigma=0.1$	-
Interest rate [%]	Normal	$\mu=0.06$	$\sigma=0.01$	-
Investment cost [%]	Uniform	$a=-0.3$	$b=0.3$	-

3.2.1. Identification of best SNG process designs

For each decision criterion, the probability to be the best process design with regard to this criterion and the probability to be part of the 5 best performing process designs (top 5) is assessed over the whole range of economic scenarios.

The results illustrated in Figure 8 clearly reveal the influence of the decision criterion on the best process design. In Figure 8 all the Pareto frontiers resulting from the multi-objective optimisation maximising the SNG equivalent efficiency and minimising the specific investment cost are illustrated. The circles represent the probability of this process design to be part of the best performing ones. The diameter of the circle is scaled in accordance with the probability. The results show that several Pareto frontiers do never enclose the best performing process designs. Different solutions emerge with the decision criteria production costs and resource profitability. The best performing process designs and the corresponding probability to be the best

one are reported in Table 7 for the different decision criteria. In terms of production costs, the process designs that lead to the lowest cost in the large range of economic scenarios belong predominately to the same Pareto corresponding to SNG production by CFB gasification with membrane cascade downstream of methanation (nb 22 - CFBO2 31 hcl). With regard to the resource profitability the best configurations are the one based on CFB gasification with Selexol absorption downstream of methanation (nb 14 - CFBO2 21 hcl), followed by the one with CFB gasification and membrane cascade downstream of methanation (nb 22 - CFBO2 31 hcl). This reveals the competition between the different CH_4 upgrading technologies and the decision criterion. The process designs with an high SNG equivalent are the ones that yield also the best economic performance even if the specific investment costs are larger than for designs with lower efficiencies, due to the profit of selling the products.

Instead of assessing the best process design only on the probability to be the best performing one with regard to a given decision criteria, the best design is now identified by the probability to be part of the top 5 performing ones (T5). In this case the selected solutions are increased as illustrated in Figure 8 and Table 8. It appears that the most economic competitive process designs for SNG production are based on CFB gasification and hot gas cleaning, and co-produce heat for district heating purposes. The different technologies for the SNG purification after methanation are in competition. When identifying the best process design with regard to the lowest production, designs with air drying (nb 10 - CFBO2 20 hcl, nb 18 - CFBO2 30 hcl) and steam drying compete (nb 14 - CFBO2 21 hcl, nb 22 - CFBO2 31 hcl)

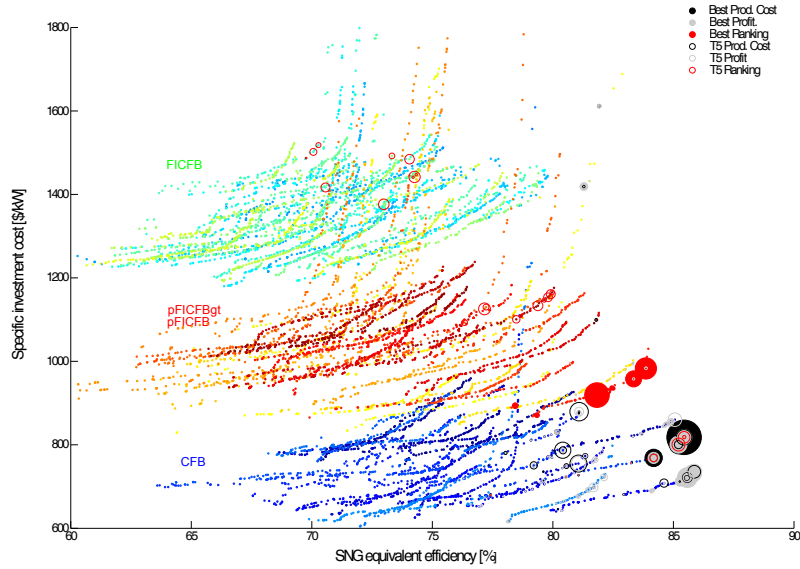


Figure 8: Pareto frontiers resulting from multi-objective optimisation of SNG processes [36] and identification of best process designs based on different decision criteria. The circles are proportional to the probability to be part of the best process designs.

with each other.

As the two different decision criteria can lead to the selection of different process designs, an overall ranking can also be established by combining the ranking of each process design with regard to the decision criteria. This allows to identify the most reliable process designs in a large range of economic scenarios. In this case, some SNG production processes based on FICFB gasification (no 101) become interesting as illustrated in Figure 8.

Taking into account the economic conditions uncertainty, the same approach can also be applied to identify the best process designs from one single Pareto or from a reduced number of technology scenarios from the SNG processes database (for example, only those with district heating, or only CFB

Table 7: Identification of the 5 best process designs in terms of production costs and resource profitability and corresponding probability to be the best performing one. The designs are characterised by XX_YY where XX is the number of the Pareto (Appendix) and YY is the number of the design in this Pareto.

Prod. Cost						
N°	Design			Proba. %	ϵ_{SNG} %	Invest. \$/kW
	Gasifier	CO ₂ capture	Drying			
22.27	CFB O ₂	Membrane	Steam	63	85.4	818
22.30	CFB O ₂	Membrane	Steam	18.3	85.2	801
22.06	CFB O ₂	Membrane	Steam	16.1	84.2	768.7
74.38	pFICFB	PSA	Air	0.8	81.3	1418.7
74.31	pFICFB	PSA	Air	0.6	81.9	1611
Profitability						
N°	Design			Proba. %	ϵ_{SNG} %	Invest. \$/kW
	Gasifier	CO ₂ capture	Drying			
14.51	CFB O ₂	Selexol	Steam	20.7	85.6	721
14.32	CFB O ₂	Selexol	Steam	15.7	85.8	731
22.30	CFB O ₂	Membrane	Steam	15.3	85.2	801
22.27	CFB O ₂	Membrane	12.9 Steam	85.4	818	
14.69	CFB O ₂	Selexol	Steam	12.0	85.8	735

with steam drying,...).

4. Conclusions

This paper presents a decision support approach that takes into account the variability of the economic conditions to identify the most economically competitive process designs from a multi-objective optimisation Pareto set. The approach is applied to systematically assess CO₂ capture options in power production processes and SNG-fuel production processes. The competition between the different process designs and the decision criteria is pointed out and the influence of the economic conditions on the decision-making is highlighted.

For CO₂ capture processes the optimal power plant design is highly in-

Table 8: Identification of the 10 best process designs in terms of production costs and resource profitability and corresponding probability to be part of the 5 best performing process designs. The designs are characterised by XX_YY where XX is the number of the Pareto (Appendix) and YY is the number of the design in this Pareto.

Prod. Cost						
N°	Gasifier	Design		Proba.	ϵ_{SNG}	Invest.
		CO ₂ capture	Drying	%	%	\$/kW
18.62	CFB O ₂	Membrane	Air	18.4	81.1	879
10.60	CFB O ₂	Selexol	Air	15.5	81.1	755
21.37	CFB O ₂	Membrane	Steam (CGCL)	14.1	80.4	787
22.27	CFB O ₂	Membrane	Steam	12.9	85.4	818
14.69	CFB O ₂	Selexol	Steam	8.6	85.9	736
14.51	CFB O ₂	Selexol	Steam	6.0	85.6	721
22.30	CFB O ₂	Membrane	Steam	3.7	85.2	801
14.15	CFB O ₂	Selexol	Steam	3.7	84.6	708
22.06	CFB O ₂	Membrane	Steam	3.2	84.2	769
21.63	CFB O ₂	Membrane	Steam (CGCL)	2.9	79.2	751
Profitability						
N°	Gasifier	Design		Proba.	ϵ_{SNG}	Invest.
		CO ₂ capture	Drying	%	%	\$/kW
22.30	CFB O ₂	Membrane	Steam	11.7	85.2	801
10.60	CFB O ₂	Selexol	Air	11.2	81.1	755
6.50	CFB O ₂	PSA	Steam	9.8	85.1	860
14.51	CFB O ₂	Selexol	Steam	7.8	85.6	721
14.69	CFB O ₂	Selexol	Steam	5.2	85.9	736
22.27	CFB O ₂	Membrane	Steam	4.3	85.4	818
18.62	CFB O ₂	Membrane	Air	4.3	81.1	879
31.51	CFB O ₂	Membrane	Steam (CGCL)	4.2	81.7	698
14.32	CFB O ₂	Selexol	Steam	3.2	85.8	732
22.06	CFB O ₂	Membrane	Steam	3.0	84.2	769

fluenced by the resource price and the introduction of a carbon tax. It is determined by the production scope and the priorities given to the different thermo-environmental criteria. By including the economic conditions sensitivity in the decision-making step, it appears that apart from the economic market conditions, the CO₂ capture rate is a key factor defining the economic competitiveness. Post-combustion CO₂ capture reveals to be economically

competitive for capture rates between 70 and 80% when a carbon tax is introduced. *This contradicts the rates up to 95% CO₂ capture that are typically recommended* . It is shown that for specific economic conditions (i.e. introduction of a carbon tax) CCS can become an energy, cost and environmental efficient alternative on the future energy market when compared to a conventional NGCC plant.

For the polygeneration of SNG, heat and power from biomass, it is revealed that the most economically competitive process design is highly influenced by the gasifier and the methane upgrading technology. *In figure 8 one can see that, considering the uncertainty analysis, the most probable best solutions lies in the right of the Pareto curve. This part of the Pareto corresponds to high efficiency (one of the objective function that is optimized) and as well high investment. This shows that for the selected economic solutions, it is important to promote the development of efficient processes even if those are more expensive. This can be explained by the benefit of selling the coproduced heat and power that adds to the produced SNG-fuel and that compensate the increase of the investment.*

The use of the uncertainty analysis method is a powerful tool to help in the identification of the best process designs by highlighting the designs that have the highest probability of being the best considering the variability of the economic conditions. Such a tool is therefore an important tool to generate a limited list of configurations to be compared.

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Appendix

SNG production process options

The database of the Pareto-optimal SNG processes' flowsheets was generated in [36]. The database consist of 118 Pareto fronts listed here below. The technology scenarios names are labeled according the following abbreviations.

- FICFB: FICFB gasification at atmospheric pressure
- pFICFB: pressurised FICFB gasification
- pFICFBgt: pressurised FICFB gasification with power recovery by expanding the flue gases in turbine
- CFBO2: pressurised CFB gasification directly heated with oxygen
- _XY: X: CO₂-removal technology (X=BN_CO2REM; 1/4: PSA downstream/upstream of methanation; 2/5: Selexol absorption downstream/upstream of methanation; 3: membrane cascade downstream methanation) Y: drying technology (Y=BN_DRY-1; 0: air drying, 1: steam drying)
- _tor: with torrefaction (i.e. BN_PYR=4, otherwise BN_PYR=0)
- _hcl: hot gas cleaning (i.e. BN_GCL=2, otherwise cold gas cleaning (BN_GCL=1))
- _nodh: without district heating (i.e. BN_DH=0, otherwise with heat cogeneration into a 110/70°C distribution grid (BN_DH=1))

Numbered list of all the technology scenarios considered for the SNG production:

1. CFBO2_10	41. FICFB_20	81. pFICFB_20
2. CFBO2_10.hcl	42. FICFB_20.nodh	82. pFICFB_20.hcl
3. CFBO2_10.hcl.nodh	43. FICFB_20.tor	83. pFICFB_20.hcl.nodh
4. CFBO2_10.nodh	44. FICFB_20.tor.nodh	84. pFICFB_20.nodh
5. CFBO2_11	45. FICFB_21	85. pFICFB_21
6. CFBO2_11.hcl	46. FICFB_21.nodh	86. pFICFB_21.hcl
7. CFBO2_11.hcl.nodh	47. FICFB_21.tor	87. pFICFB_21.hcl.nodh
8. CFBO2_11.nodh	48. FICFB_21.tor.nodh	88. pFICFB_21.nodh
9. CFBO2_20	49. FICFB_30	89. pFICFB_30
10. CFBO2_20.hcl	50. FICFB_30.nodh	90. pFICFB_30.hcl
11. CFBO2_20.hcl.nodh	51. FICFB_30.tor	91. pFICFB_30.hcl.nodh
12. CFBO2_20.nodh	52. FICFB_30.tor.nodh	92. pFICFB_30.nodh
13. CFBO2_21	53. FICFB_31	93. pFICFB_31
14. CFBO2_21.hcl	54. FICFB_31.nodh	94. pFICFB_31.hcl
15. CFBO2_21.hcl.nodh	55. FICFB_31.tor	95. pFICFB_31.hcl.nodh
16. CFBO2_21.nodh	56. FICFB_31.tor.nodh	96. pFICFB_31.nodh
17. CFBO2_30	57. FICFB_40	97. pFICFBgt_10
18. CFBO2_30.hcl	58. FICFB_40.nodh	98. pFICFBgt_10.hcl.nodh
19. CFBO2_30.hcl.nodh	59. FICFB_40.tor	99. pFICFBgt_10.nodh
20. CFBO2_30.nodh	60. FICFB_40.tor.nodh	100. pFICFBgt_11
21. CFBO2_31	61. FICFB_41	101. pFICFBgt_11.hcl
22. CFBO2_31.hcl	62. FICFB_41.nodh	102. pFICFBgt_11.hcl.nodh
23. CFBO2_31.hcl.nodh	63. FICFB_41.tor	103. pFICFBgt_11.nodh
24. CFBO2_31.nodh	64. FICFB_41.tor.nodh	104. pFICFBgt_20
25. CFBO2_40	65. FICFB_50	105. pFICFBgt_20.hcl
26. CFBO2_40.nodh	66. FICFB_50.nodh	106. pFICFBgt_20.hcl.nodh
27. CFBO2_41	67. FICFB_50.tor	107. pFICFBgt_20.nodh
28. CFBO2_41.nodh	68. FICFB_50.tor.nodh	108. pFICFBgt_21
29. CFBO2_50	69. FICFB_51	109. pFICFBgt_21.hcl
30. CFBO2_50.nodh	70. FICFB_51.nodh	110. pFICFBgt_21.hcl.nodh
31. CFBO2_51	71. FICFB_51.tor	111. pFICFBgt_21.nodh
32. CFBO2_51.nodh	72. FICFB_51.tor.nodh	112. pFICFBgt_30
33. FICFB_10	73. pFICFB_10	113. pFICFBgt_30.hcl
34. FICFB_10.nodh	74. pFICFB_10.hcl	114. pFICFBgt_30.hcl.nodh
35. FICFB_10.tor	75. pFICFB_10.hcl.nodh	115. pFICFBgt_30.nodh
36. FICFB_10.tor.nodh	76. pFICFB_10.nodh	116. pFICFBgt_31
37. FICFB_11	77. pFICFB_11	117. pFICFBgt_31.hcl.nodh
38. FICFB_11.nodh	78. pFICFB_11.hcl	118. pFICFBgt_31.nodh
39. FICFB_11.tor	79. pFICFB_11.hcl.nodh	
40. FICFB_11.tor.nodh	80. pFICFB_11.nodh	