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Economic feasibility of calcium looping under uncertainty

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ABSTRACT

An emerging calcium looping process has been shown to be a promising alternative to solvent scrubbing, which is regarded as the most mature CO_2 capture technology. Its retrofits to coal-fired power plants have the potential to reduce both energy and economic penalties associated with the mature CO_2 capture technologies. However, these conclusions have been made based on the deterministic outputs of the economic models that have not considered uncertainties in the model inputs. Therefore, this study incorporates a stochastic approach into the economic analysis of the retrofit of such emerging CO_2 capture technology to the coal-fired power plant. The stochastic analysis revealed that levelised cost of electricity (LCOE) and specific total capital requirement were highly affected by the uncertainty in the input variables to the process and economic models. The most probable values for these key economic performance indicators were shown to fall between 75 and 115 €/MW_{el}h, and 2100 and 2300 €/$kW_{el,gross}$, respectively. Interestingly, the most probable LCOE values for the coal-fired power plant will fall between 50 and 150 €/MW_{el}h. This indicated that the calcium looping retrofit scenario can become economically favoured, mainly due to the high economic penalties incurred by unabated coal-fired power plant associated with carbon tax. Importantly, the outputs of the stochastic economic assessment aligned well with the deterministic results reported in the literature. As the latter were generated using different sets of assumptions regarding the process and economic models, the stochastic approach to the economic assessment can minimise the impact of the model assumptions on estimates of the key economic parameters. Moreover, by indicating the probability of particular outputs, as well as ranking the model input variables according to their influence on the key economic performance, such analysis would allow making more insightful decisions regarding further funding

and development of the calcium looping process. Finally, use of the stochastic approach in the economic feasibility assessment enables a more profound and reliable comparison of the different calcium looping retrofit configurations, as well as benchmarking different CO_2 capture technologies.

Key Words: Uncertainty, probabilistic analysis, coal-fired power plant, process modelling and simulation, techno-economic analysis, calcium looping

1 INTRODUCTION

To significantly reduce the risks and impacts associated with climate change, the mean temperature increase needs to be held well below 2°C and efforts to limit it to 1.5°C above pre-industrial levels need to be pursued [1]. Carbon capture and storage (CCS) technologies are expected to be essential for reducing the environmental impact of the power sector in the short- to mid-term [2], which is one of the major CO_2 emitters due to a large share of coal-fired power plants in the global power generation fleet [3–5]. CCS has been shown to be the least cost-intensive option for decarbonisation of the power sector that would enable achieving the desired emission reduction levels by 2050. This is primarily because of the high capital requirement of the alternative technologies, such as geothermal power plants and offshore wind farms [2,6]. Importantly, large-scale deployment of CCS is expected to reduce wholesale electricity prices in the UK by up to 15% by 2030 compared to a no-CCS scenario [6]. Also, lack of CCS in the power sector will require 40% higher capital cost to achieve more than 50% reduction of the global energy-related CO_2 emissions by 2050 relative to 2009 (IEA 2°C scenario) [2].

Post-combustion CO_2 capture technologies are regarded as the key class of CCS technologies for decarbonisation of the power sector, as they can be both easily retrofitted to the existing and integrated with the new-built coal-fired power plants [7,8]. Chemical solvent scrubbing using amine-based solvents, such as monoethanolamine (MEA), piperazine (PZ) or methyldiethanolamine (MDEA), is currently perceived as the most mature CO_2 capture technology that will probably be a first choice technology for decarbonisation of coal-fired power plants [9–11]. However, despite the recent developments in chemical solvent scrubbing [12], retrofits of such technologies are predicted to reduce the net thermal efficiency of the entire system by 7–13% points

[10,13,14]. A calcium looping process, which is based on the reversible carbonation reaction of lime with CO_2, is considered as an emerging CO_2 capture technology [15] and has already been demonstrated at a scale of 1.9 MW_{th} [13]. Integration of this process to the coal-fired power plant has been shown to impose a net efficiency penalty of 5–8% points [13,16], which is lower compared to the figures reported for the mature CO_2 capture technologies. As a result, it has been estimated that the cost of CO_2 avoided corresponding to the calcium looping retrofits has a potential to be lower (7–87.5 €/tCO_2) [17–23] compared to that of the mature chemical solvent scrubbing (35–75 €/tCO_2) [24–27]. Therefore, calcium looping is perceived as an emerging CO_2 capture technology that could reduce both energy and economic penalties associated with the mature CO_2 capture technologies.

However, predictions of the economic performance indicators for retrofits of post-combustion CO_2 capture technologies to coal-fired power plants have been only obtained using deterministic models. Although such approach can provide the point estimates of the economic performance indicators under any set of assumptions, these models do not consider the uncertainty in the input variables and are highly sensitive to selection of the particular set of assumptions. As the initial values for inputs to economic models, such as capital costs, fuel prices, carbon tax, and cost of CO_2 transport and storage, can vary significantly depending on the considered economic environment [28], the deterministic nature of such model predictions does not provide a definitive representation of the actual system's economic performance. Importantly, around 40% of the mega-projects across different industries, which are usually defined as developments costing more than 1 billion USD, experience cost overruns [29]. This was also the case for the Kemper County and Boundary Dam projects that exceeded the initial cost estimation by a factor of 3 and 1.15, respectively [30,31]. Importantly, the costs of the former project may further increase, as the unit is not yet operational. For this reason, the credibility of economic model prediction can be improved by considering the effect of uncertainty in the model inputs to generate the best- and the worst-case scenario estimates, as well as the probabilistic distributions of the economic model outputs.

An application of stochastic analysis to techno-economic assessment of the engineering systems has been shown to provide a more profound insight into operation and techno-economic performance of these systems [32–38]. As indicated above, the economic performance of the calcium looping retrofits has been only assessed using a deterministic approach, which does not account for the uncertainties in the model inputs. For this reason, this study incorporates the stochastic approach into the economic analysis of the retrofit of such emerging CO_2 capture technology to the coal-fired power plant. This is achieved by combining a robust approximation model of the retrofitted system using a robust artificial neural network, which is developed from a finite number of deterministic simulations in Aspen Plus®, and the economic model with the Monte Carlo simulation. It is expected that by considering the effect of uncertainties on the prediction of the key economic performance indicators, such as levelised cost of electricity (LCOE) and specific total capital requirement, this analysis would contribute to a more profound understanding of the system's economics, and thus its viability. Furthermore, an effect of variation in the key statistical parameters of the input variables, such as mean and extreme values, is analysed to identify the key input variables affecting the economic performance of the calcium looping process retrofit.

2 PROCESS MODEL DESCRIPTION

2.1 Supercritical coal-fired power plant

The 580 MW_{el} supercritical coal-fired power plant, which has a net thermal efficiency of 38.0%$_{HHV}$, is used as a reference in this study. A process model of this unit has been previously developed in Aspen Plus® [39,40] based on, and validated with data presented in, the revised NETL report [41]. The considered coal-fired power plant comprises a power boiler, with NO_x and SO_x emission control equipment, as well as an electrostatic precipitator. In the power boiler, heat from the combustion of coal is utilised to raise high-pressure steam for the reheated regenerative steam cycle. The steam generator comprises primary, secondary, and reheat superheaters, as well as an economiser. The live (242.3 bar) and reheat steam (45.2 bar) raised in these sections leave the power boiler at a temperature of 593.3°C, and are fed to the steam turbine section that comprises high- (HP), intermediate- (IP), and low-pressure (LP) extraction condensing steam turbines. To improve the efficiency of the steam cycle, a part of the steam from the turbine sections is drawn to feed the main feedwater heating train. This subsystem consists of five LP feedwater heaters, the last of which is called a deaerator and is a mixed feedwater heater, and three HP feedwater heaters.

2.2 Calcium looping post-combustion CO_2 capture plant

A calcium looping process is considered in this study for decarbonisation of the conventional 580 MW_{el} coal-fired power plant. A process model for this unit has been developed in Aspen Plus® by Hanak et al. [42] and its prediction was found to be in good agreement with the experimental data at different flue gas loads.

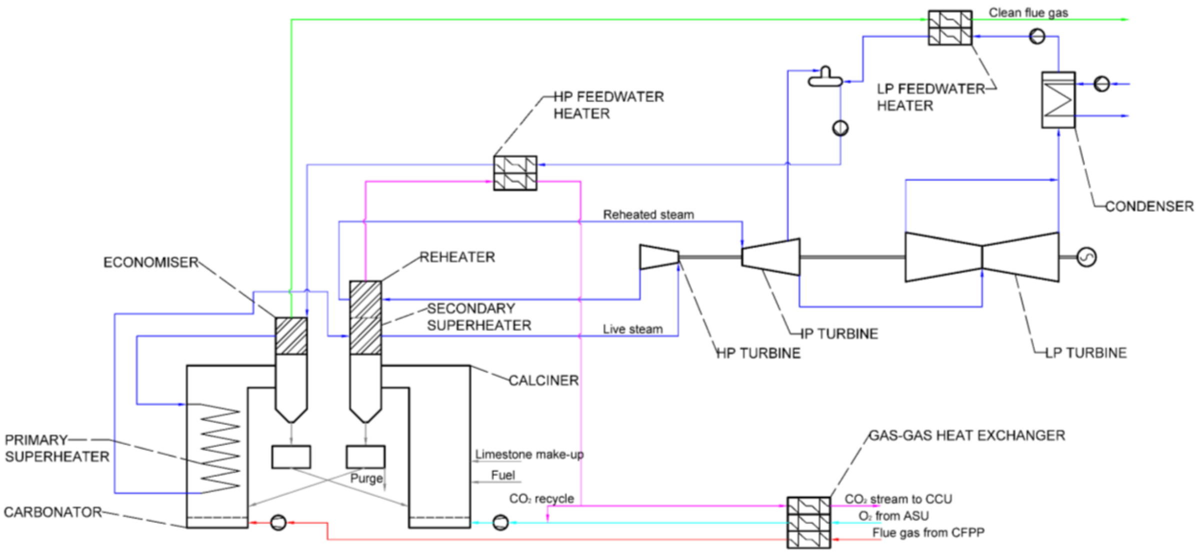

Figure 1: Process flow diagram of the calcium looping process for decarbonisation of the conventional 580 MW$_{el}$ coal-fired power plant

The calcium looping process (Figure 1) comprises a carbonator, which is modelled as a stoichiometric reactor, and a calciner, which is modelled as a Gibbs reactor. To sustain the endothermic calcination reaction and ensure the high purity of CO_2 leaving the calciner, an additional amount of coal is combusted in an O_2/CO_2 environment directly in this reactor. The coal decomposition is modelled using a yield reactor. The average sorbent conversion in the carbonator is estimated using the semi-empirical correlation shown in Eq. (1), which was derived by Rodríguez et al. [43], and the sorbent deactivation curve derived from experimental tests at the 1.7 MW$_{th}$ La Pereda pilot plant [44]. In this correlation, the maximum average conversion of sorbent is a function of the carbonation (f_{carb}) and calcination extent (f_{calc}), sorbent characteristics (a_1, a_2, f_1, f_2, b), fraction of never-calcined limestone in the system (r_0), fresh limestone make-up (F_0) and solid looping rate (F_R). Moreover, the equilibrium partial pressures of CO_2 in the gas streams leaving the carbonator and the calciner are determined using correlation by Baker [45], to account for the equilibrium limitations.

$$\mathrm{X}_{ave} = (F_0 + F_R r_0) f_{calc} \left[\frac{a_1 f_1^2}{F_0 + F_R f_{carb} f_{calc} (1 - f_1)} + \frac{a_2 f_2^2}{F_0 + F_R f_{carb} f_{calc} (1 - f_2)} + \frac{b}{F_0} \right] \quad (1)$$

The high-grade heat available in the carbonator and the process streams is utilised to raise high-pressure steam for the secondary steam cycle of similar operating characteristics to the one in the conventional 580 MW_{el} coal-fired power plant.

3 STOCHASTIC ECONOMIC ASSESSMENT

3.1 Economic analysis methodology

The economic performance of the calcium looping retrofit to the conventional 580 MW_{el} coal-fired power plant is assessed in terms of the levelised cost of electricity *(LCOE)* that is estimated using Eq. (2) [19,20,46].

$$LCOE = \frac{TCR \times FCF + FOM}{\dot{W}_{net} \times CF \times 24 \times 365} + VOM + \frac{SFC}{\eta_{th}} \quad (2)$$

This parameter correlates the thermodynamic performance indicators of the retrofitted system, such as net power output, net thermal efficiency, and capacity factor (*CF*), with its economic performance indicators, such as total capital requirement (*TCR*), variable (*VOM*) and fixed (*FOM*) operating and maintenance costs, specific fuel cost (*SFC*), and the fixed charge factor (*FCF*), which considers the system's lifetime and project discount rate. In this analysis, the total capital requirement includes the capital cost of both the reference coal-fired power plant and the calcium looping process. The capital cost of the reference coal-fired power plant is determined using the exponential method function [47]. Conversely, the capital cost of the calcium looping process (C_{CaL}) is estimated using the correlation developed by Romano et al. [17] and represented by Eq. (3). This approach considers the capital cost for an oxy-fuel circulating-fluidised bed system as the reference capital cost (C_0) [48], as well as allows taking into account the volume of the reactors (*V*), the heat input in the calciner

(Q_{calc}), along with the corresponding scaling factors, and the fraction of the total cost of the calciner associated with the heat transfer surfaces (α).

$$C_{CaL} = C_0 \left[\alpha \left(\frac{Q_{calc}}{Q_{0,calc}} \right)^{SF,Q} + (1-\alpha) \left(\frac{V_{calc}}{V_{0,calc}} \right)^{SF,V} + (1-\alpha) \left(\frac{V_{carb}}{V_{0,carb}} \right)^{SF,V} \right] \quad (3)$$

The fixed and variable operating and maintenance costs are expressed as a fraction of total capital cost, while operating costs associated with fuel and sorbent consumption, CO_2 storage and transport, and CO_2 emission are determined based on process simulation outputs and specific costs of these components.

3.2 Stochastic assessment methodology

The economic performance of the calcium looping process retrofit is dependent upon the assumptions in both the process and economic models. Although the deterministic models can provide a reliable prediction of the system's performance under any operating conditions, these models do not consider the stochasticity of the input variables that can be seen in the actual engineering systems and economic environments. Therefore, the deterministic economic assessment conducted according to the methodology presented in Section 3.1 does not provide a definitive representation of the actual system's performance that is often subjected to random fluctuations in the external and internal operating conditions [49]. To account for the uncertainty in the model input variables, the stochastic approach is adapted to the economic analysis methodology (Figure 2).

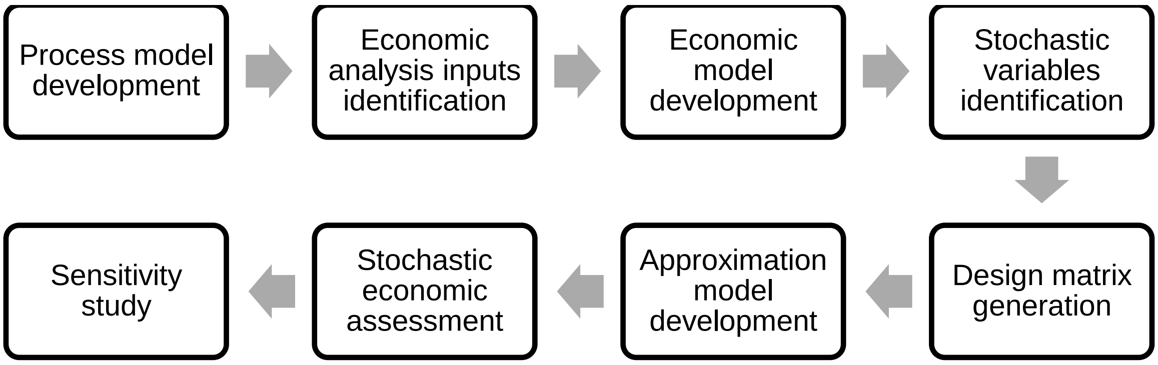

Figure 2: Overview of the stochastic economic assessment framework

The stochastic economic assessment framework employed in this study can be seen as a variation of the probabilistic performance assessment framework proposed by Hanak et al. [35,36], and comprises eight definitive stages. In the first stage, the process model has been developed in Aspen Plus® [42] and validated with the data available in the literature [44]. Next, the inputs from the process model to the economic analysis are identified, and then the economic model is built in MATLAB. Afterwards, the stochastic variables in both the process and economic models, as well as their statistical representation are identified. Then, similarly to the probabilistic performance assessment performed in the earlier studies by Hanak et al. [35,36], the approximation model is developed based on the design matrix generated using the process model. Conversely to the process model, the economic model is much less computationally demanding, and thus it can be directly used in the stochastic economic assessment, even with a large number of iterations. In the next step, the stochastic economic assessment is conducted using the Monte Carlo simulations to generate the probability density curves for the key economic performance indicators including the LCOE and the specific total capital requirement. This is achieved by estimating the values of the key economic performance indicators using the input dataset that contains one million entries that have been randomly generated according to the assumed distributions of the input variables. Finally, the sensitivity study is performed to assess the effect of the key statistic parameters of the stochastic variables, which include the mean value for the normally distributed variables and the extreme values for the uniformly distributed variables, on the key economic performance indicators.

3.3 Identification of stochastic variables

Having analysed both the process and economic models, the stochastic input variables have been categorised into process, scale and size, and economic variables (Table 1). First, the thermodynamic performance of the calcium looping retrofit is mainly sensitive to four process variables including the relative fresh sorbent make-up rate, O_2 content in the calciner inlet gas stream, O_2 content in the calciner outlet gas stream, which determines the excess O_2 in the calciner, and the CO_2 capture level in the carbonator [18,23,42,50–52]. These input variables are assumed to be normally distributed with the statistic parameters determined from the literature [32,34,53,54].

Secondly, the size of the equipment in the calcium looping retrofit scenario is dependent upon selection of the scaling factors and operating conditions. It is assumed that the scaling factors are normally distributed with the coefficient of variation of 5% [32,34]. Conversely, the superficial velocity in, and the height-to-diameter ratio of, the fluidised beds are assumed to be uniformly distributed, as the optimum specifications have not been yet identified. Therefore, the minimum and maximum values are identified from the literature [13,55,56].

Finally, the economic performance of the calcium looping retrofit scenario is dependent upon the economic variables related to the operating costs, reference specific capital costs, and the project characteristics. Most of these variables are assumed to be normally distributed [32,34], with exception of the carbon tax and the specific cost of CO_2 transport and storage. As the carbon tax may vary between 10–

150 €/tCO_2 [57,58] and specific cost of CO_2 transport and storage/utilisation may vary between -15–40 €/tCO_2 [23,24], depending on whether CO_2 is stored or utilised, for example, for enhanced oil recovery, the mean value for these variables is uncertain. Therefore, these variables are assumed to be uniformly distributed.

Table 1: Stochastic variables and their distribution

Variable	Distribution	Nominal value	Variation*
Process variables			
Relative fresh sorbent make-up rate (mole basis) [53,54]	Normal	0.05	20%
O_2 content in calciner inlet gas stream (mole basis) [32,34]	Normal	0.3	5%
O_2 content in calciner outlet gas stream (mole basis) [32,34]	Normal	0.025	2.5%
CO_2 capture level (-) [32,34]	Normal	0.9	2.5%
Scale and size variables			
Scaling factor of coal-fired power plant (-) [32,34]	Normal	0.67	5%
Scaling factor for the heat transfer surfaces (-) [32,34]	Normal	0.85	5%
Scaling factor for the heat rate in the calciner (-) [32,34]	Normal	0.9	5%
Scaling factor for volume of the reactors (-) [32,34]	Normal	0.67	5%
Superficial velocity (m/s) [13,55]	Uniform	5	2–14
Height-to-diameter ratio (-) [56]	Uniform	3	2–4
Economic variables			
Variable operating and maintenance cost rate (%/year) [32,34]	Normal	2	10%
Fixed operating and maintenance cost rate (%/year) [32,34]	Normal	1	10%
Carbon tax (€/tonne) [57,58]	Uniform	30	10–150
Specific cost of CO_2 transport and storage (€/tonne) [23,24,59,60]	Uniform	7	-15–40
Specific cost of sorbent (€/tonne) [32,34]	Normal	6	25%
Specific cost of coal (€/GJ) [32,34]	Normal	1.5	25%
Project discount rate (%) [32,34]	Normal	8.78	10%
Capacity factor (%) [32,34]	Normal	80	7%
Reference specific capital cost of coal-fired power plant (€/kW) [32,34]	Normal	1100	10%
Reference specific capital cost of calcium looping process (€/kW) [32,34]	Normal	1252.3	10%

*Coefficient of variation for normal distribution and a range for uniform distribution

3.4 Stochastic response surface approximation model using artificial neural network

The process models developed in Aspen Plus® cannot be directly used to provide the process input to the stochastic economic assessment, because a large number of iterations required in the stochastic analysis would require a high computational demand. For this reason, this study utilises the deterministic process model described in Section 2 to generate the design matrix that is, in turn, used to develop the robust approximation model. Such model will link the process input variables to the process models with the process output variables, the latter of which will be considered as input variables to the economic model. The design matrix* used in this study comprises 32 entries of the process input variables required by the economic analysis resulting from the following variation of the stochastic process variables:

- Relative make-up rate was varied between 0.02 and 0.1;
- O_2 content in the calciner inlet gas stream was varied between 0.3 and 0.95;
- O_2 content in the calciner outlet gas stream was varied between 0.005 and 0.045;
- CO_2 capture level in the carbonator was varied between 0.7 and 0.9.

The earlier studies by Hanak et al. [35,36] utilised the generic quadratic multi-variable polynomial (MVR) model shown in Eq. (4) as the approximation model.

$$\tilde{g}(u) = a + \sum_{i=1}^{n} b_i \cdot u_i + \sum_{i=1}^{n} c_i \cdot u_i^2 \tag{4}$$

However, such an approximation model would need to be derived for each of the process output variables that are required in the economic model. Moreover, the quadratic MVR may struggle to accurately represent nonlinear characteristics of the process model [61]. For this reason, this study utilises the artificial neural network (ANN) to accurately link the process inputs to the process model with the process inputs to the economic model.

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*The design matrix is provided in the Supplementary Information.

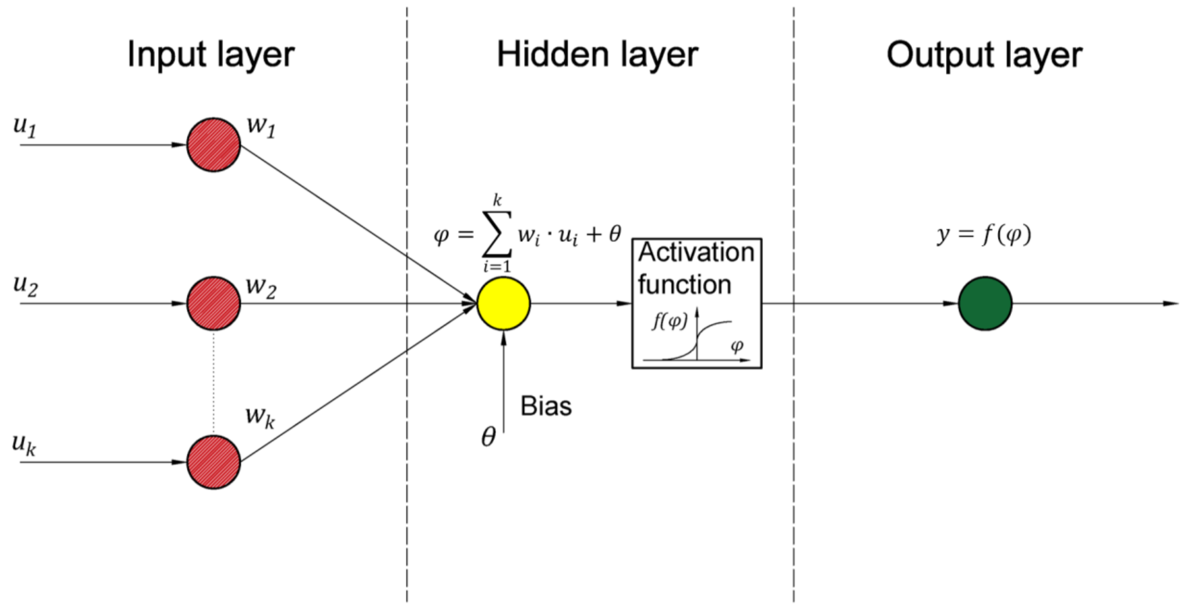


Figure 3: Nonlinear model of a sigmoid neuron (Adapted with permission from Oko et al. [62] and Kalogirou [63]. Copyright 2017, Elsevier)

The ANN is inspired by the structure of biological neural networks and the process they utilise to solve problems [62]. As opposed to the conventional approximation models, ANN learns the relations between the inputs and outputs by training [64]. It is also known to be able to reliably represent multiple outputs considering multiple inputs [63], even if the system's behaviour is highly nonlinear [64]. The most common structure of the ANN is shown in Figure 3 and comprises an input layer, one hidden layer with sigmoid neurons, and an output layer with linear neurons [64,65]. The input to each neuron can be the network input from the input layer, the output of the neuron in the previous layer, and an externally applied bias [62]. The output of each neuron is the function of the weighted sum of the neuron inputs, with the hyperbolic tangent sigmoid transfer function shown in Eq. (5) used in the hidden layer and the linear function shown in Eq. (6) used in the output layer. The weights and bias are determined in the training process by minimising error between the ANN outputs and the design matrix.

$$f(\varphi) = \frac{2}{1 + \mathrm{e}^{-2\left(\sum_{i=1}^{k} w_i \cdot u_i + \theta\right)}} - 1 \tag{5}$$

$$f(\varphi) = \sum_{i=1}^{k} w_i \cdot u_i + \theta \tag{6}$$

Using the MATLAB Neural Network Fitting toolbox, a two-layer feed-forward ANN with ten sigmoid hidden neurons and linear output neurons (Figure 4) is developed to map the design matrix generated using the process model. To ensure an accurate prediction by the ANN, the data in the design matrix were randomly divided between training (70%), validation (15%) and testing (15%) samples. Moreover, the number of the hidden neurons has been selected to be higher than the number of the ANN output parameters. In the considered scenario of the calcium looping process retrofit, eight process variables are required to conduct the economic analysis as presented in Figure 4. Therefore, ten sigmoid hidden neurons are considered. The weights and bias in the ANN have been determined using the Levenberg-Marquardt backpropagation algorithm with Bayesian regularisation, as it is expected to result in good representation of nonlinear and small datasets.

To ensure that the ANN accurately predicts the thermodynamic performance of the calcium looping retrofit, its performance is benchmarked against the data matrix generated using the process model developed in Aspen Plus® and compared to the predictions of the approximation model based on the generic quadratic MVR. With four input and eight output variables, there are thirty-two directional outputs to be considered. For this reason, a representative sample was selected and is evaluated in this section (Figure 5), while the information on all directional outputs is presented along with the design matrix in the Supplementary Information. Analysis of the selected directional outputs (Figure 5) revealed that the ANN used in this study is capable of mapping the thermodynamic performance of the calcium looping retrofit accurately, despite its nonlinear characteristic. Importantly, the ANN was shown to outperform the generic quadratic MVR that tends to perform well only in representing linear and slightly nonlinear outputs. In strongly nonlinear cases, however, the latter approximation model tends to predict the general trends, but not the actual values. Therefore, the ANN is deemed to represent the design matrix more accurately and is used in the stochastic economic assessment.

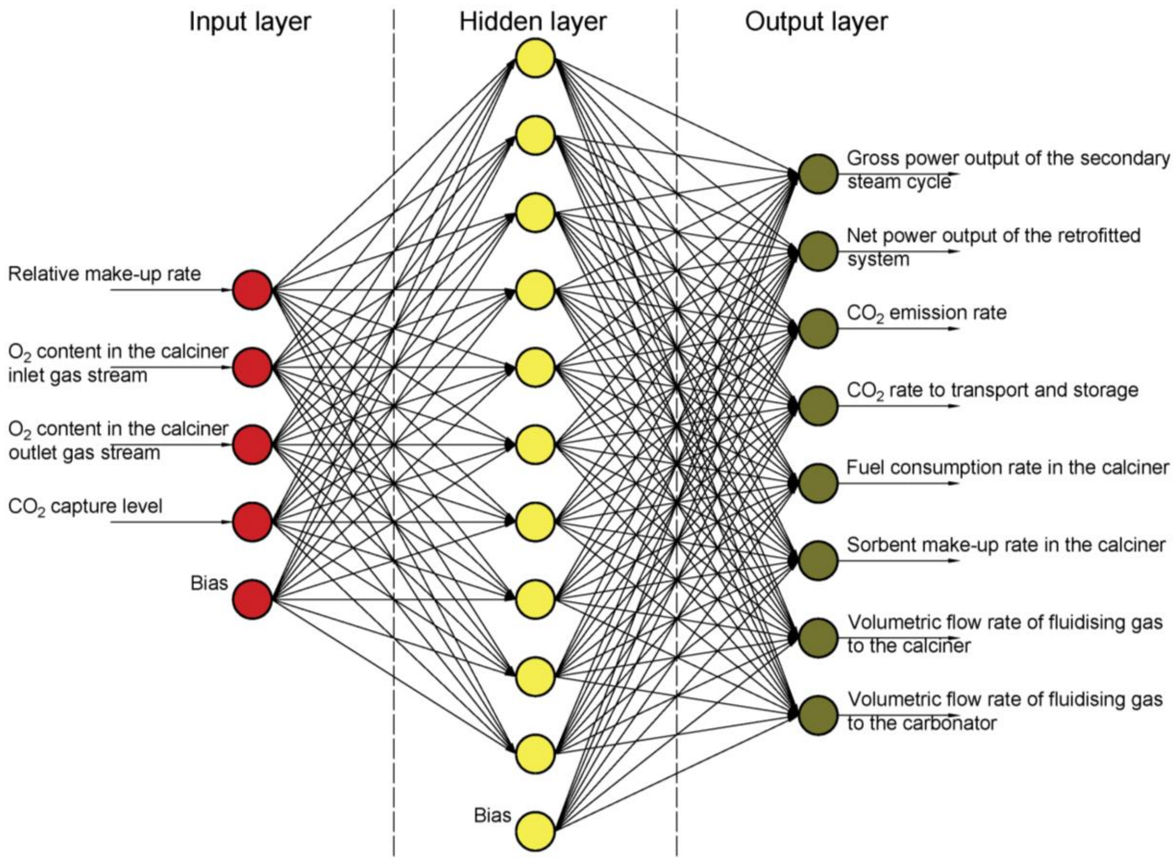


Figure 4: Structure of the artificial neural network used to map the thermodynamic performance of the calcium looping process retrofit

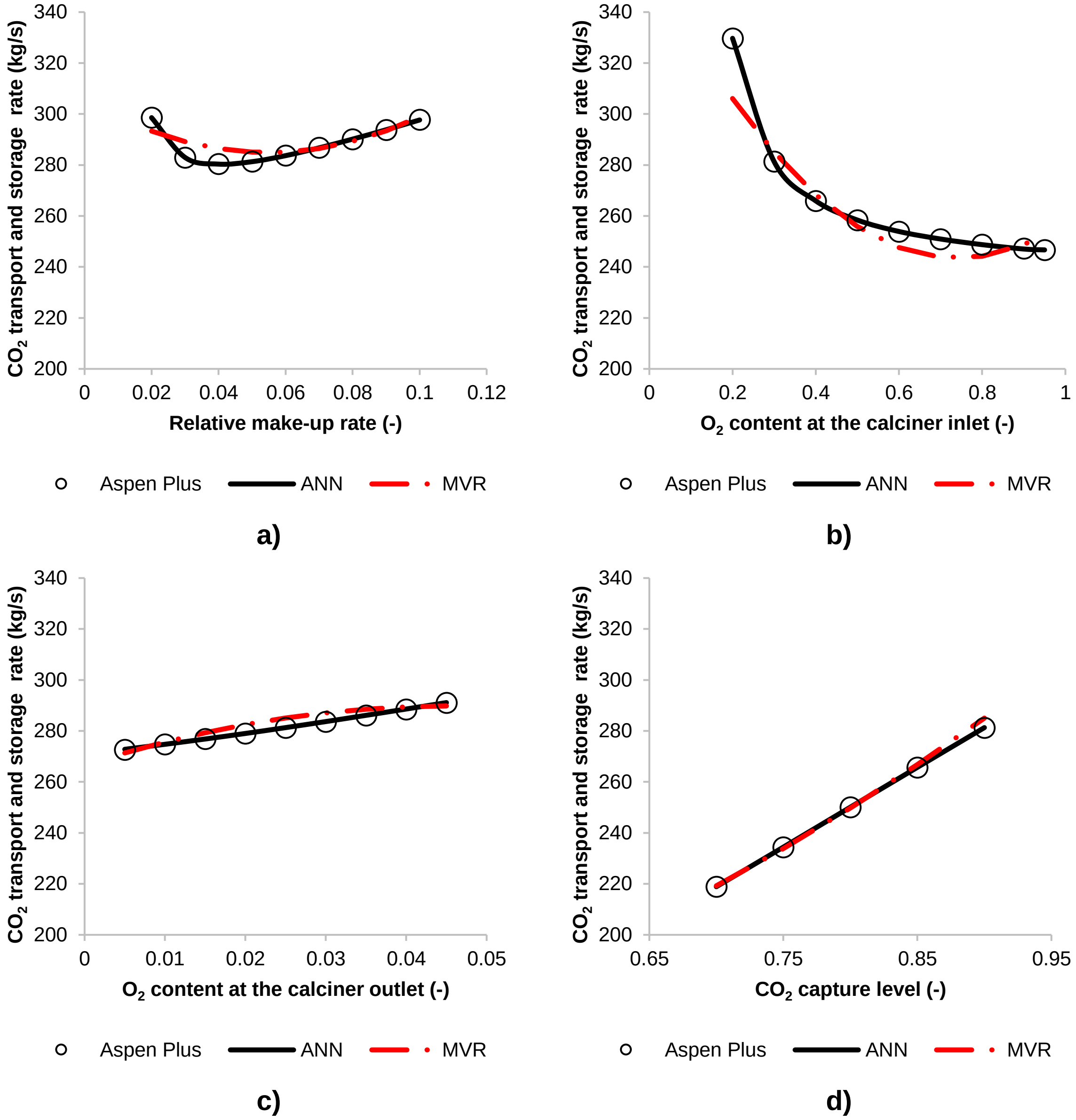


Figure 5: Comparison of the directional outputs for CO_2 transport and storage rate generated using artificial neural network (ANN), quadratic multi-variable polynomial (MVR) and Aspen Plus®

4 ECONOMIC PERFORMANCE ASSESSMENT

4.1 Effect of uncertainty on levelised cost of electricity

The LCOE is considered as one of the key economic performance indicators for the power generation systems, including CCS retrofits, as it indicates the unit cost of electricity that is required to cover the lifetime costs of the entire system. The effect of uncertainty on the LCOE of the reference coal-fired power plant (reference scenario) and the calcium retrofit scenario (retrofit scenario) is presented in Figure 6. The analysis has revealed that the statistical distribution of the LCOE is close to uniform and normal distribution in the reference and retrofit scenario, respectively. In both cases, elongated regions of the highest probability density can be observed, but it is considerably longer in the former case; hence, the distribution of the LCOE in the reference scenario is close to uniform distribution. This is caused by the fact that the uniform distribution has been assigned to some of the stochastic variables, which in the reference scenario have a high influence on the LCOE. It has been also estimated that the mean value of the LCOE in the reference scenario is 95.6 €/MW_{el}, with the figures for the 5th and 95th percentile estimated to be 41.6 and 149.6 €/$MW_{el}h$, respectively. Interestingly, the mean value of the LCOE associated with the calcium looping process retrofit has been estimated to be lower (92.5 €/$MW_{el}h$), with the figures for the 5th and 95th percentile estimated to be 59.0 and 126.2 €/$MW_{el}h$, respectively. Lower figures for the mean value and 95th percentile of the LCOE in the latter case indicate that even in the worst-case scenario, the calcium looping retrofit can become more feasible than the reference coal-fired power plant, especially in light of expected increase of the carbon tax. Importantly, the distribution of the LCOE in the retrofit scenario aligns well with the deterministic values for the LCOE from a range of cases reported in previous studies [17–23], all of which have been overlaid onto the probability density curve in Figure 6. Importantly, these deterministic values can be mostly classified as the best-case (25.8–54.3 €/$MW_{el}h$) [18–20] and probable-case (68.4–82.5 €/$MW_{el}h$) [17,19–22] scenarios, while a limited number of studies represent the worst-case scenario (116.7 €/$MW_{el}h$) [23]. The stochastic economic assessment indicated that the most probable figure for the LCOE for the considered calcium looping process retrofit falls between 75 and 115 €/$MW_{el}h$.

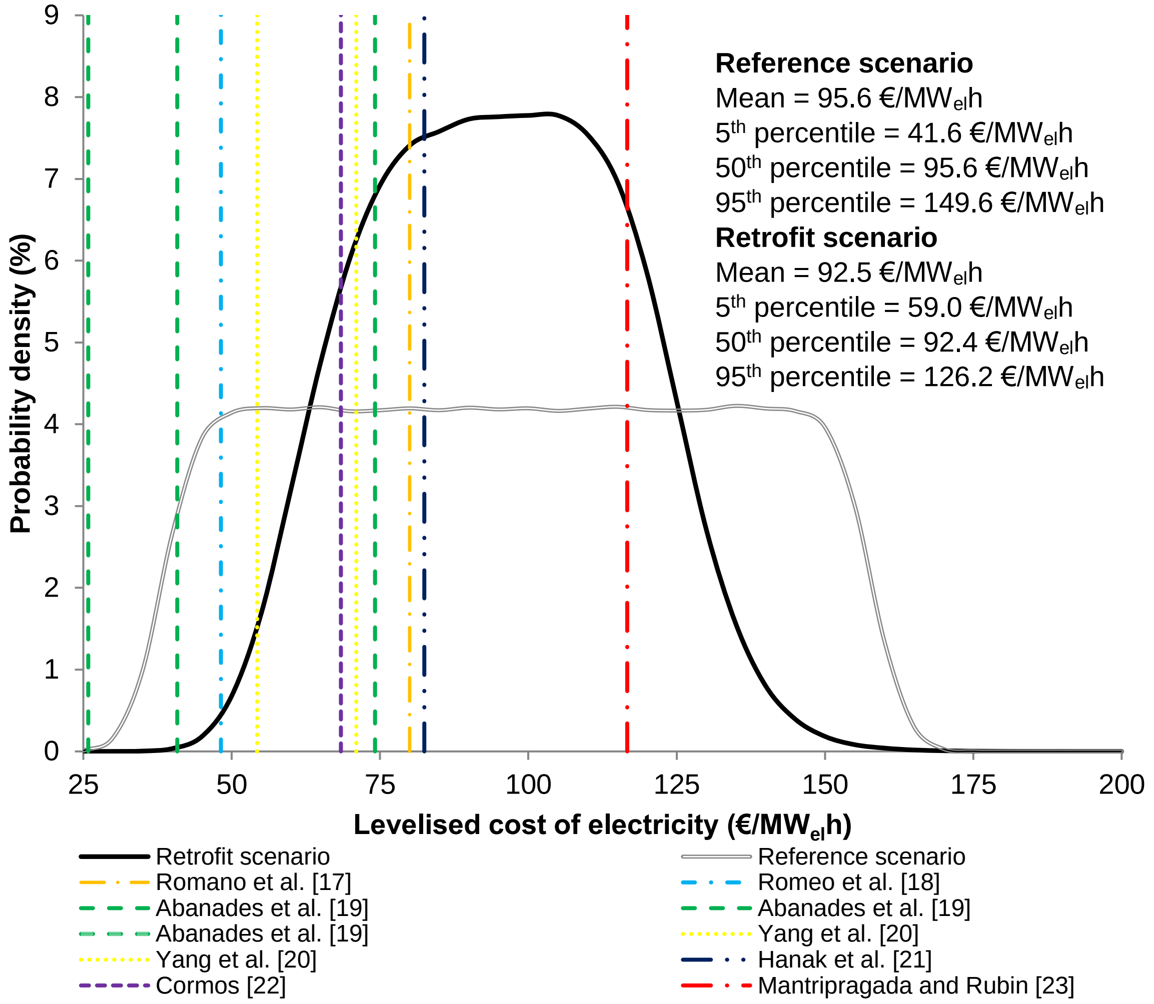
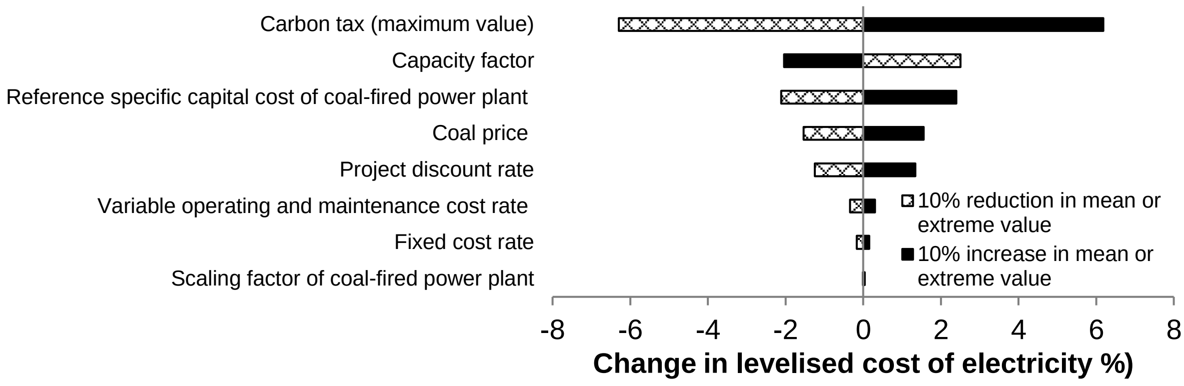
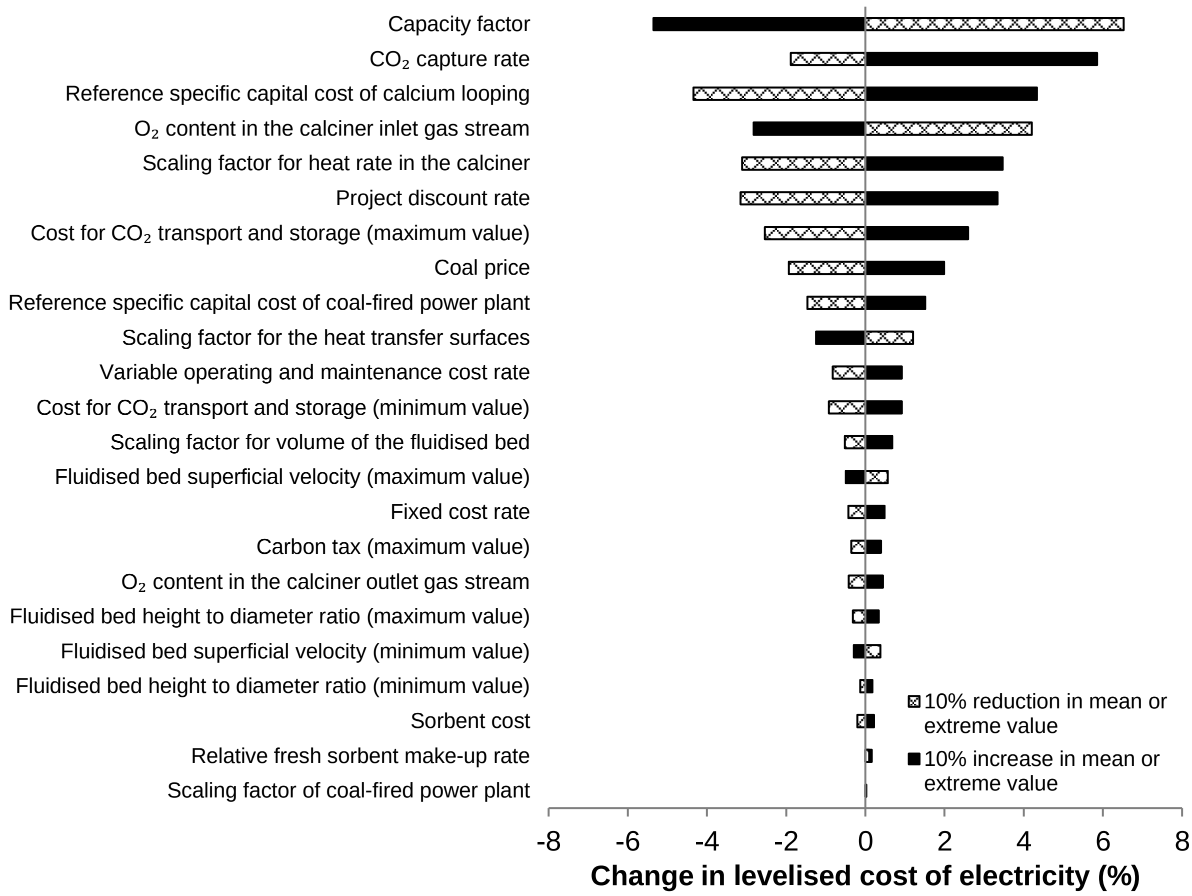


Figure 6: Effect of uncertainty on the levelised cost of electricity



a)



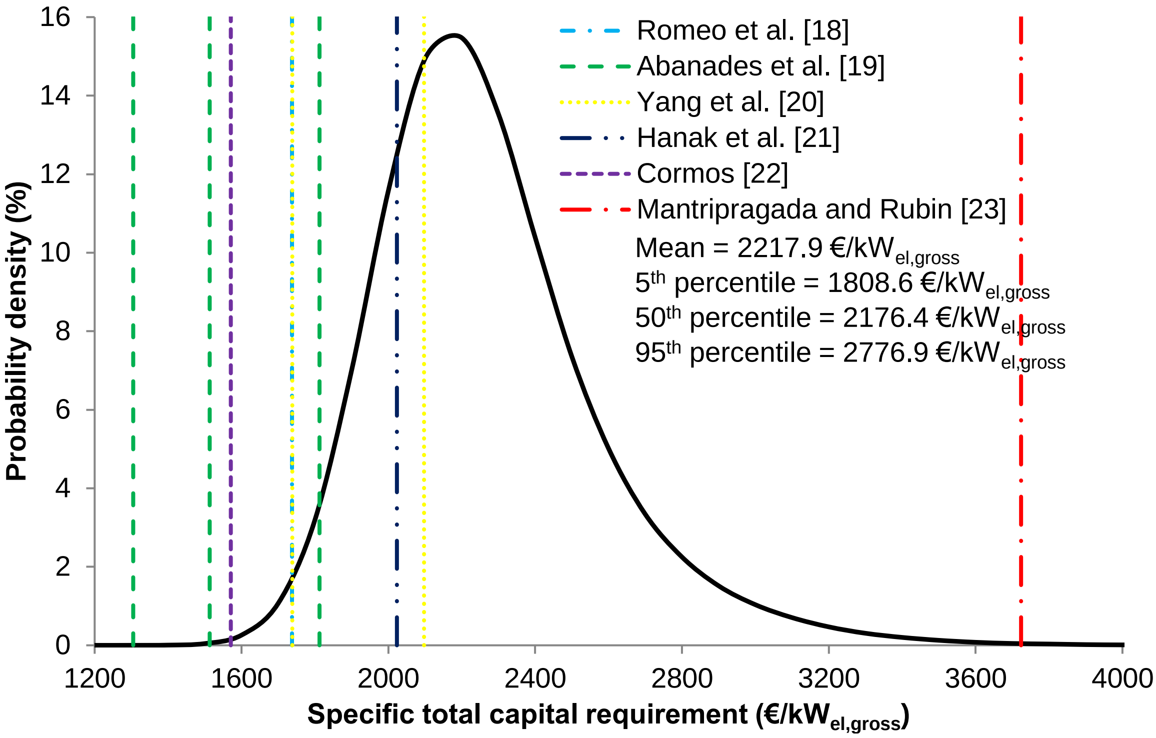
b)

Figure 7: Effect of key statistic parameters sensitivity on the levelised cost of electricity in the a) reference and b) retrofit scenario

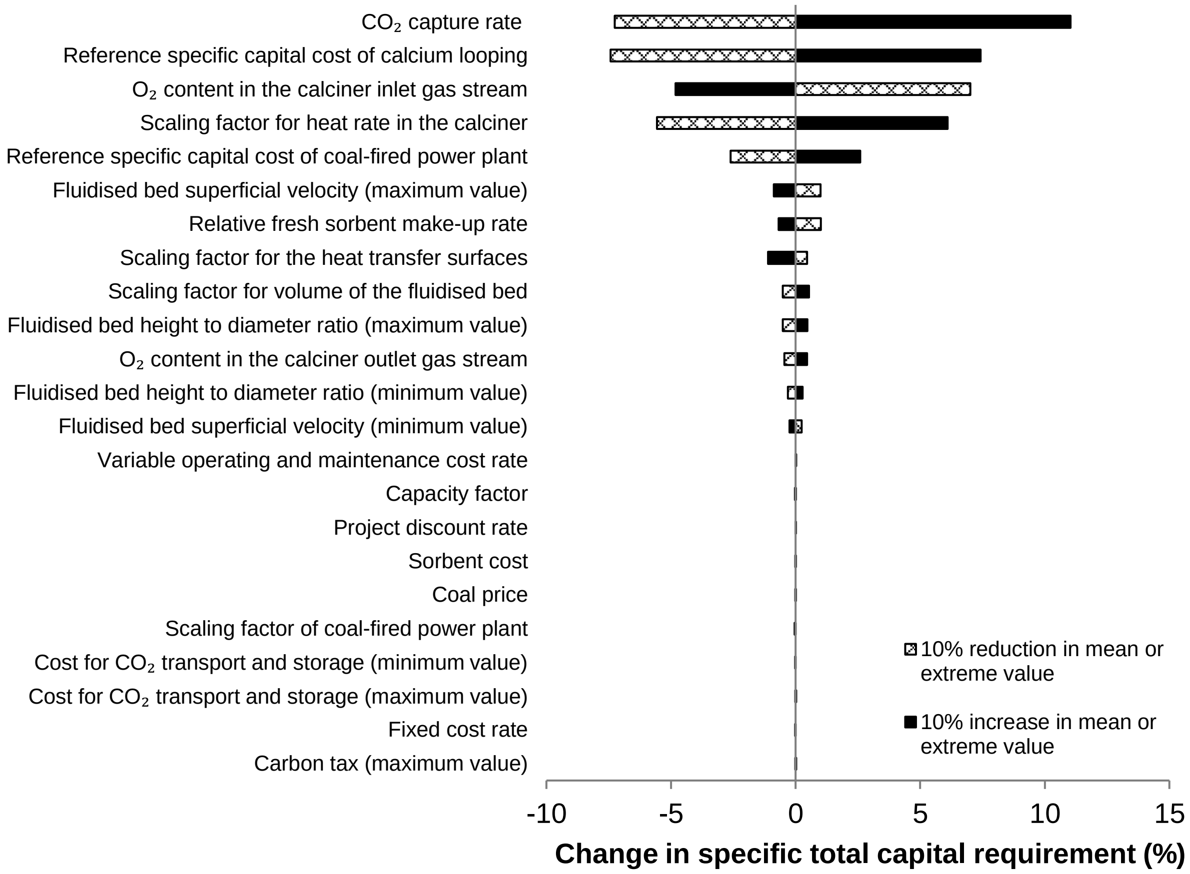
The sensitivity analysis performed on the key statistic parameters of the selected stochastic variables (Figure 7a) has indicated that the LCOE in the reference scenario is mostly sensitive to the carbon tax. Change of ±10% in the maximum value of this parameter resulted in the LCOE varying between -5.4% and 6.5%. This is due to the economic penalties that can be associated with CO_2 emissions and that increase with carbon tax. Importantly, the LCOE varied by ±2% on change in capacity factor, reference specific capital cost of coal-fired power plant, coal price and project discount rate, but was found to be rather insensitive to variable and fixed cost rates, as well as the scaling factor of coal-fired power plant. Furthermore, the analysis (Figure 7b) has indicated that the LCOE in the retrofit scenario is equally sensitive to the economic, process, as well as scale and size variables. In contrast to the reference scenario, it has been observed that the capacity factor had the highest influence on the LCOE, as it varied by -5.3% and 6.5% on 10% change in the mean value of the capacity factor. This can be directly associated to the amount of electricity generated over the project lifetime, and thus low capacity factor would result in low amount of electricity generated and high LCOE. Furthermore, a 10% increase in the mean value of the CO_2 capture level in the carbonator resulted in 5.9% increase in the LCOE, which can be associated with the extra capacity of the calcium looping process. It needs to be stressed that such high CO_2 capture level (>95%) may not be achievable under the assumed operating conditions in the carbonator due to the equilibrium limits. Importantly, a 10% decrease in the mean value of the CO_2 capture level in the carbonator resulted in only 1.9% reduction in the LCOE. This can be associated with more CO_2 being emitted into the atmosphere, and thus the benefit of the reduced capital cost requirement is diminished by an additional expenditure on carbon tax, which increases as the CO_2 capture level decreases. Interestingly, a 2.9% reduction in the LCOE can be achieved on a 10% increase in the mean value of the O_2 content in the calciner inlet gas stream. This indicates that operating the calciner with reduced recycle of the CO_2 stream may improve the economic performance of the entire system, providing that no hot-spots occur in the calciner causing excessive degradation of the sorbent. Moreover, both the reference specific capital cost of the calcium looping process and the scaling factor for the heat rate in the calciner were found to have a significant effect on the LCOE, as a 10% increase in their mean values resulted in a 4.4 and 3.5% increase in the LCOE, respectively. This can be directly associated with an increase in the total capital requirement. Finally, the LCOE was shown to vary by more than ±1% on variation in the mean values of the economic variables, such as reference specific capital cost of coal-fired power plant, project discount rate, cost of CO_2 transport and storage, as well as the maximum value of the coal price. The variations in the remaining stochastic variables, including the carbon tax, have been shown to have a minor or negligible effect on the LCOE.

4.2 Effect of uncertainty on specific total capital requirement

In addition to the LCOE, the specific total capital requirement, which indicates the unit capacity cost, can be considered as an important parameter in assessment of the economic feasibility of the CCS retrofits. The stochastic analysis has shown that, opposed to the LCOE, the specific total capital requirement is a slightly positively-skewed normal distribution (Figure 8a). This is primarily caused by the exponential correlation between the equipment cost and the stochastic variables, and the fact that the stochastic variables with uniform distribution do not have a significant influence on the specific total capital requirement (Figure 8b). The analysis has shown that the mean value of the specific total capital requirement is 2217.9 €/$kW_{el,gross}$ and it ranges between 1808.6 (5^{th} percentile) and 2776.9 €/$kW_{el,gross}$ (95^{th} percentile). Importantly, the 50^{th} percentile value was estimated to be 2176.4 €/$kW_{el,gross}$, which, as opposed to the LCOE, differs from the mean value considerably, and thus, it represents the value of the specific total capital requirement with the highest probability. Comparing the results of the stochastic economic analysis with those in the literature, it can be noted that most of the studies used the best-case estimate of the specific total capital requirement (1305–1738.4 €/kW$_{el,gross}$) [18–20,22], with fewer studies using the probable-case estimate (1812.5–2097.3 €/kW$_{el,gross}$) [19–21]. Importantly, a limited number of studies considered the worst-case estimate (3723.9 €/kW$_{el,gross}$) [23] that is more than double the 5th percentile value, as well as 1.7 and 1.3 times higher than the 50th and 95th percentile values, respectively, estimated in this study. As indicated in Section 4.1, the capital requirement has a significant effect on the estimation of the LCOE. As a result of considering the worst-case estimate of the specific total capital requirement, the key economic performance indicators of the calcium looping retrofit are higher compared to the mean values estimated in this study using the stochastic approach and the deterministic values reported in the literature that were based on best- and probable-case estimates. It needs to be stressed, however, that although the stochastic economic assessment indicated that the most probable figure for the total capital requirement of the calcium looping retrofit falls between 2100 and 2300 €/kW$_{el,gross}$, the probability that it would be higher than 3500 €/kW$_{el,gross}$ has been estimated to be 0.2%.



a)



b)

Figure 8: Effect of a) uncertainty and b) key statistic parameters sensitivity on the specific total capital cost requirement

As opposed to the LCOE, the sensitivity analysis performed on the key statistic parameters of the selected stochastic variables (Figure 8b) showed that the specific total capital requirement is mainly sensitive to the process variables, such as CO_2 capture level and the O_2 content in the calciner inlet gas stream. On the one hand, the largest variation was observed on a 10% variation in the mean value of the CO_2 capture level in the carbonator, as it was shown to result in the specific total capital requirement varying by -7.2 to 11.1%. This is directly related to the size of the equipment required to achieve desired CO_2 capture level. On the other hand, a 10% increase in the mean value of the O_2 content in the calciner inlet gas stream was found to reduce the specific total capital requirement by 4.8%. This arises from smaller size of the calciner due to reduced requirement for the CO_2 recycle. It is important to point out that the main economic variables that affect the specific total capital requirement are the reference specific capital cost of the calcium looping process and the coal-fired power plant. The variation in the remaining stochastic variables have been shown to have a minor or negligible effect on the specific total capital requirement.

4.3 Contribution to deployment of calcium looping process

The economic assessment using the stochastic approach employed in this study allowed predicting the envelopes for the system's key economic performance indicators under uncertain process and economic input conditions. The outcome of such analysis identified the economic performance of the considered system that can be classified as the worst-, probable-, and the best-case scenarios corresponding to 95th, 50th, and 5th percentile, respectively. Furthermore, by considering a large number of the stochastic variables, both from the process and the economic model, the stochastic economic assessment can rank the model input variables according to their influence on the key economic performance indicators. Therefore, by considering the uncertainty in the process and economic model inputs, the stochastic economic assessment will provide the most probable estimate for the key economic performance indicators and thus will provide a valuable input to the investment decision-making process.

The results of the stochastic economic analysis presented in Section 4 are in agreement with the wide range of the deterministic outcomes from the studies reported in the literature. It needs to be stressed, however, that the studies reported in the literature were conducted with different sets of assumptions regarding the thermodynamics of the reference coal-fired power plant and the operating conditions of the calcium looping process, as well as the economic assumptions. The fact that these deterministic results align well with the outcomes of the stochastic economic assessment conducted in this study implies that such approach can alleviate the impact of the assumptions on the economic estimates, and thus, by indicating the probability of particular outputs, it would allow making more insightful decisions regarding further funding and development of the calcium looping process. Furthermore, such an approach would allow considering the effect of the uncertainty in the external factors, such as fuel characteristics, marked energy demand, and ambient conditions, on the techno-economic feasibility of such low-carbon power generation systems. In turn, this would allow drawing more accurate conclusions on the process feasibility and operability under uncertain conditions within the entire energy network. Such analysis was, however, out of this study scope.

Finally, employing the stochastic analysis in the techno-economic feasibility assessment allows undertaking a more profound comparison across the different process configurations as well as benchmarking the calcium looping process against other CO_2 capture technologies. Such analysis would allow drawing more realistic conclusions, as inclusion of the uncertainty in the analysis yields the probability of the particular outputs.

5 CONCLUSIONS

This study employed the stochastic approach, which considers the effect of uncertainty on the predictions of the process and economic models, to assess the economic feasibility of the calcium looping retrofit to the 580 MW_{el} supercritical coal-fired power plant. The stochastic economic analysis revealed that the key economic performance indicators, such as the LCOE and specific total capital requirement, are highly affected by uncertainty in the input variables to the process and economic models. The stochastic analysis revealed that the LCOE for the calcium looping process retrofit were nearly normally distributed with a slightly elongated region of the highest probability density. The most probable values of this key economic performance indicator fell between 75 and 115 €/MW_{el}h, respectively. Importantly, the most probable values of the LCOE for the reference coal-fired power plant were shown to be between 50 and 150 €/MW_{el}h, and this parameter was found to be strongly affected by the carbon tax. Conversely, the specific total capital requirement for the calcium looping retrofit scenario was shown to have a slightly positively-skewed normal distribution, and its most probable values were shown to fall between 2100 and 2300 €/$kW_{el,gross}$.

The sensitivity analysis performed on the key statistic parameters of the selected stochastic variables revealed that the LCOE is mostly sensitive to the capacity factor, CO_2 capture level in the carbonator, O_2 content in the calciner inlet gas stream, project discount rate, coal price, scaling factor for the heat rate in the calciner, as well as the reference specific capital cost of both calcium looping and the reference coal-fired power plant. The specific total capital requirement was found to be sensitive mostly to

CO_2 capture level in the carbonator, O_2 content in the calciner inlet gas stream, scaling factor for the heat rate in the calciner, as well as the reference specific capital cost of both calcium looping and the reference coal-fired power plant. Such outputs allowed ranking the stochastic input variables according to their influence on the key economic performance indicators.

A comparison between the deterministic data and the outputs of the stochastic economic analysis indicated that most of the results reported so far in the literature can be classified as the best- or probable-case scenarios that correspond to the 5th or 50th percentile of the key economic performance indicators, respectively. A limited number of studies was classified as the worst-case scenario (95th percentile), which was associated to a high estimate of the specific total capital requirement, the probability of which was estimated to be lower than 0.2%. This had influenced the deterministic estimation of the LCOE, which was, therefore, classified as worst-case scenario. This was a result of this key economic performance indicator being sensitive to the reference specific capital cost of both calcium looping and coal-fired power plant. Nevertheless, as the outputs of the stochastic economic assessment align well with the deterministic results reported in the literature, which were generated using different sets of assumptions regarding the process and economic models, such approach to the economic assessment can alleviate the impact of the model assumptions on the economic estimates. Moreover, by indicating the probability of particular outputs, it would allow making more insightful decisions regarding further funding and development of the calcium looping process. Furthermore, use of the stochastic approach in the economic feasibility assessment enables a more profound and reliable comparison of the different calcium looping retrofit configurations, as well as benchmarking different CO_2 capture technologies.

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NOMENCLATURE

a	Multi-variable polynomial parameter	-
a_1	Li et al. [33] model fitting parameter	-
a_2	Li et al. [33] model fitting parameter	-
b	Li et al. [33] model fitting parameter	-
b_i	Multi-variable polynomial parameter	
C_0	Reference capital cost of calcium looping process	€/kW$_{el}$
CF	Capacity factor	-
c_i	Multi-variable polynomial parameter	
e_{CO_2}	Specific CO_2 emission	gCO_2/kW$_{el}$h
EP	Net efficiency penalty	%$_{HHV}$ points
f	Neuron activation function	
F_0	Fresh-limestone make up rate	kmol/s
f_1	Li et al. [33] model fitting parameter	-
f_2	Li et al. [33] model fitting parameter	-
f_{calc}	Calcination reaction extent	-
f_{carb}	Carbonation reaction extent	-
FCF	Fixed charge factor	-
FOM	Fixed operating and maintenance cost	€
F_R	CaO looping rate	kmol/s
$\tilde{g}$	Dependent variable	-
$LCOE$	Levelised cost of electricity	€/MW$_{el}$h
$\dot{m}_{CO_2}$	Rate of CO_2 emission	kg/s
SCF	Specific fuel cost	€/MW$_{ch}$h
SF,Q	Scaling factor for reactor heat input	-
SF,V	Scaling factor for reactor volume	-
TCR	Total capital requirement	€
$Q_{0,calc}$	Reference heat input to the calciner	MW$_{th}$
Q_{calc}	Heat input to the calciner	MW$_{th}$
r_0	Fraction of never calcined limestone in the system	-
V	Volume of reactors	m^3
V_0	Reference volume of reactor	m^3
VOM	Variable operating and maintenance cost	€/MW$_{el}$h
u_i	Stochastic variable	-
w_k	Artificial neural network node weight	-
$\dot{W}_{net}$	Net power output of the integrated system	MW$_{el}$
X_{ave}	Average sorbent conversion	-
y	Artificial neural network output	-
α	Fraction of the total cost of a circulating fluidised bed reactor associated with the heat transfer surfaces	-
η_{th}	Net thermal efficiency	-
η_b	Boiler thermal efficiency	-
θ	Artificial neural network layer bias	-
φ	Neuron output	-

ABBREVIATIONS

ANN	Artificial neural network
CCS	Carbon capture and storage
CCU	CO_2 compression unit
HP	High-pressure
IP	Intermediate-pressure
LCOE	Levelised cost of electricity
LP	Low-pressure
MEA	Monoethanolamine
MDEA	Methyldiethanolamine
MVR	Multi-variable polynomial
PZ	Piperazine