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A Novel Stochastic Market Potential Optimisation Model for Clean Technology Uptake Modelling

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ABSTRACT

The high mitigation cost of clean innovations, warrants policy support for increased uptake. This study applies optimization techniques to investigate the impact of market-based policies in generating sufficient demand pull to trigger cost reduction under uncertainty. A novel Stochastic Market Potential Optimization model (SMPOM) is developed to maximize the cost difference between the initial cost of a technology and the new cost using a market-based policy. The model is applied to a case study of carbon capture and storage (CCS) in 32 integrated steel plants in Europe. Results show policy induced demand pull can reduce the mitigation cost of CCS.

Keywords: Clean technology uptake modelling, market-based policy design, carbon capture and storage, Carbon tax, uncertainties using stochastic programming, Market Potential assessment

NONMENCLATURE

Abbreviations	
CCS	Carbon capture and storage
GHGs	Greenhouse gases
EIIs	Energy intensive industries
IAM	Integrated assessment models
MPA	Market potential analysis
EU ETS	EU emissions trading system
SMPOM	Stochastic market potential optimisation model
Symbols	
n	Year
L_r	Learning rate
ε	CO_2 emission (t/yr)
ω	CO_2 tax ($/t)
A	Cumulative CO_2 capture (t/yr)
φ	Market share
γ	CO_2 capture rate
β	Market occupancy
U_{C0}	Initial cost of capture ($/t)
A_0	Initial CO_2 captured (t/yr)
σ	Standard deviation
x	Mean
U_C	New cost of capture

1. INTRODUCTION

1.1 Background

There is a strong consensus that interventions in form of policies, especially market-based instruments/fiscal instruments have supported the uptake of clean technologies by addressing the highest ranked barriers (high initial capital costs/large upfront investment). Examples of policy support are carbon taxation, feed-in schemes, and the EU Emissions Trading Scheme (EU ETS). In 2022, carbon tax in the UK was $23.65 per ton, while Sweden was $129.89 per ton making it the highest among European countries [1]. Even though carbon taxes have risen year-on-year from 2020, uptake of clean technologies especially CCS is still very low, and there is still no way to quantify their impact on generating demand-pull for CCS in heavy industry. Effective policy instruments achieve technology uptake by lowering financial barriers to a point where demand pull for the technology is created. Uncertainties in key elements required to formulate adequate policy support for clean technology uptake would be a critical challenge for their development [2]. Key elements of uncertainties are the technology learning rate (measures reduction in cost for every doubling of capacity), performance, value

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of policy support for example carbon tax, and technology cost. Learning rates for CCS range from 3% to 14%, and the performance (capture rate) of commercially available post-combustion CCS technologies range from 63% to 73%.

Globally, the iron and steel sector are responsible for 11% of carbon dioxide emissions and 7-9% of GHGs emissions. The iron and steel sector also provides primary raw materials for the manufacture of clean technologies to decarbonize the entire economy; hence decarbonising the iron and steel sector is important. Post-combustion Carbon Capture and Storage (CCS) has been identified as a key technology to decarbonize steel production and is the most suitable due to ease of retrofitting into existing integrated steel plants [3]. Hence the focus of this study. There is no existing methodology to quantify the impact of policy support in generating sufficient demand for CCS in integrated steel plants to trigger reduction in capture cost under several uncertainties. Existing models for clean technology policy assessment and uptake are not sufficient.

1.2 Literature Review

A cleantech like CCS has been considered as the most suitable mitigation technology for integrated iron and steel plants [3]. As CCS plays an important role in decarbonizing iron and steel plants, reducing the mitigation cost to accelerate CCS adoption becomes necessitated. Modelling Carbon Capture and Storage (CCS) technology for techno-economic analysis [3], developing advanced configurations [4], analyzing different solvents [5], and carbon dioxide condensation [6] have been the main focus of current research on CCS integration in iron and steel plants. The financial barrier of CCS adoption, the necessity of business model and policies frameworks are constantly emphasized to increase uptake of CCS in most of existing studies. Yet, no studies have quantified the impact of policies to reduce CCS cost, and generate sufficient market pull to sustain cost reduction based on the technology learning from a market perspective, all under uncertainty. The field of clean technology uptake modelling under uncertainty is still new.

When it comes to uncertainty, the focus of previous studies has been the technology characteristics. For example, Lee et al. [7] conclude that major challenges in designing CCS networks are variability of construction, operation cost, unpredictable events, permeability and porosity of reservoir, and fluctuation of carbon dioxide emission level of each source, which are technological uncertainties in CCS. In addition, porosity and permeability are the key parameters as the available capacity of reservoir may change orders of magnitude compared to the predicted one [8]. Han et al. [9] investigated the uncertainty in estimating carbon dioxide emissions as it is released from multiple sources from changing environments using stochastic programming. Stochastic programming is an optimization model where some of parameters are uncertain and can be illustrated by probability distribution. Bistline et al. [10] examined the influence of heat rate in CCS plants which affects carbon dioxide emissions. In addition to technological uncertainties, Vrijmoed et al. [11] studied the influence of policies by performing sensitivity analysis. A model was built to evaluate various policy scenarios such as carbon prices, CCS subsidies, and feed-in tariffs. However, their work did not quantify the impact of policies in creating a demand pull as it was done for a single plant. Koelbl et al. [12] investigated impacts of uncertainties in techno-economic parameters. Again, the impact of policies in generating sufficient demand to drive down costs was still not considered. The study of learning rate effects sheds light on how quickly a technology can improve and how it develops based on market developments. The carbon dioxide capture rate has a significant impact on electricity and carbon dioxide mitigation cost, it is necessary to gain insight into the future trends of carbon dioxide capture rate.

The aim of this research is to develop a novel stochastic technology uptake optimization model which provides insight into the impact of policies in reducing the cost of clean technologies by generating sufficient demand, and the model will be applied to CCS uptake in 32 integrated steel plants in Europe. With stochastic optimization, the uncertain parameters are illustrated by probability distribution. The aim is not to design the CCS plant; hence a generic model is used. The novel stochastic optimization model maximizes the cost difference between the initial carbon capture cost and new carbon capture cost due to policy implementation. This research can help in quantifying the impact of policy intervention, to increase industry's confidence in adopting clean technologies like CCS. This study is the first to demonstrate how policies reduce cost and generate sufficient demand for CCS to trigger further cost reduction under uncertainty.

2. METHODS

The multi-layer methodology involves a sensitivity analysis in Section 2.1 to define which uncertain parameters have larger impact on the objective function, a probability distribution acquisition in Section 2.2 to replace the certain parameters in the deterministic model with normally distributed uncertain parameters, and this is then used to build the stochastic optimization model in Section 2.3. The number of scenarios can be further determined (Section 2.4) by a trade-off between tractability issues and problem representation issues in the stochastic model.

2.1 Sensitivity Analysis

The uncertain parameters such as initial carbon dioxide captured, learning rate, initial capture cost, carbon dioxide capture rate, and carbon dioxide emissions per plant, etc. are allowed to vary by 0~20%, etc. to illustrate which parameter has larger effect on the objective function based on the deterministic representation of the problem. Results show the CCS learning rate and carbon dioxide capture rate have the highest impact. As a result, uncertainty to learning rate and capture rate are conducted in this study.

2.2 Probability distribution acquisition

As mentioned, stochastic programming requires probability distributions of the uncertain variables. Normal distribution plays an important role in engineering, genetics, statistics, social and natural sciences, etc. often used to describe real-value random variables whose distributions are not known. The central limit theorem from probability theory may explain why the independent random variables tend to be normally distributed, which establishes that a random variable, Y, the sum of independent random variables will also be normally distributed. As a result, probability distribution of learning rate and carbon dioxide capture rate are assumed to be normally distributed. Normal distribution contains two key parameters: mean and standard deviation. After acquisition of learning rate and capture rate samples, mean and standard deviation are obtained from the normal distribution calculator.

2.3 Novel Stochastic Market Potential Optimisation Model

The stochastic programming model is built in Pyomo which is a Python-based open-source optimisation model. The SMPOM optimisation model is provided in Equation (1)-(5). The objective function is to maximize the cost difference between initial CO_2 capture cost and the cost after uptake of CCS from increased demand (Eq. 1). New cost of capture is obtained by cumulative CO_2 capture (A) and learning parameter (B) shown in Eq. (2) to Eq. (4), respectively. In our model, initial CO_2 capture cost and initial CO_2 captured is set to be 55.4085 ($/t) and 10000000 (t/yr.), respectively. The cumulative CO_2 capture is due to increased demand. After combining Eq. (1) to Eq. (4), the formulation of the objection function is represented by Eq. (5). Equation (6) makes sure carbon tax impact on cost is smaller than zero to incentivize uptake of CCS. Carbon tax impact on cost is equal to carbon capture cost at 63% capture rate minus tax to pay for each plant shown in Equation (7). Currently, the highest carbon tax is $129.89 in Sweden [1]. Therefore, the highest carbon tax is set to be $130 in Equation (8). In addition, the carbon tax is the degree of freedom/operational variable in our model. Equation (9) ensures market share (Eq. 11) obtained from the model does not exceed market occupancy (Eq. 10). By reformulating Eq. (3), market share for each plant can be shown in Eq. (11) and it only exists when Eq. (6) is satisfied. The stochastic model is built by replacing the fixed parameters with random variables which probability distributions are obtained in Section 3.1. The equations below (Eq. 12 and Eq.13) show the stochastic model. To generate 200 scenarios, “for i in range (200)” is written at the first line of the stochastic model where i represents the number of iterations.

$$max\ \ U_{C0} - U_C \tag{1}$$

$$U_C = U_{C0}\left(\frac{A}{A_0}\right)^{-B} \tag{2}$$

$$A = A_0 + \gamma \sum_{i=1}^{32} \varphi_i \sum_{i=1}^{32} \varepsilon_i \tag{3}$$

$$B = \frac{log\ (1-L_r)}{log\ (2)} \tag{4}$$

$$min\ U_{C0}\left[1 - \left(\frac{A_0 + \gamma \sum_{i=1}^{32} \varphi_i \sum_{i=1}^{32} \varepsilon_i}{A_0}\right)^{\frac{log\ (1-L_r)}{log\ (2)}}\right] \tag{5}$$

$$\varepsilon_i(U_{C0} - \gamma\ \omega_i) \leq 0 \quad i = 1, \ldots, 32 \tag{6}$$

$$U_{C0}\varepsilon_i - 0.63\varepsilon_i\omega \leq 0 \quad i = 1, \ldots, 32 \tag{7}$$

$$\omega_i - 130 \leq 0 \quad i = 1, \ldots, 32 \tag{8}$$

$$\varphi_i - \beta_i \leq 0\ i = 1, \ldots, 32 \tag{9}$$

$$\beta_i = \frac{\varepsilon_i}{\sum_{i=1}^{32} \varepsilon_i}\ i = 1, \ldots, 32 \tag{10}$$

$$\sum_{i=1}^{32} \varphi_i = \frac{A - A_0}{\gamma \sum_{i=1}^{32} \varepsilon_i} \tag{11}$$

$$\gamma = np.random.normal(x_\gamma, \sigma_\gamma) \tag{12}$$

$$L_r = np.random.normal(x_{L_r}, \sigma_{L_r}) \tag{13}$$

2.4 Scenarios determination

The number of scenarios is determined to stabilize the objective function. Each scenario represents a real circumstance with a random learning rate and a random capture rate. Then, for each scenario, the model provides one optimal value and a carbon tax. the objective value becomes stable at 200 scenarios making it a suitable and acceptable number. Thus, the number of scenarios is set to be 200 in this research.

3. RESULTS AND DISCUSSION

The data collected for this research includes the cost of capture for CCS technologies applicable to integrated steel plants, the emissions reduction potential of these technologies, the number of integrated steel plants in the EU, the location of each plant, the steel production capacity of the plants, and the carbon intensity of steel. The model is applied to investigate the adoption of 30% MEA Post Combustion Capture with 63% capture rate from blast furnace in 32 iron and steel plants across the EU (Table A.1 in the Appendix). Another novelty of this work is the application of the stochastic model to 32 integrated steel plants in Europe. Results from the stochastic optimization are compared with the deterministic equivalent, as accounting for uncertainty could lead to better outcomes.

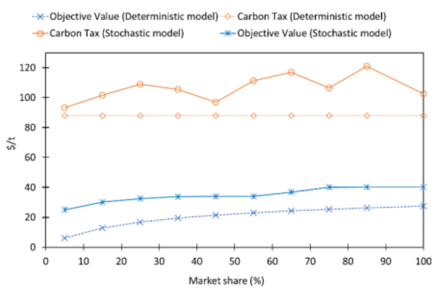

Fig. 1. Impact of market uptake on objective value for stochastic and deterministic model

The demand for CCS in integrated steel plants is denoted by the market share; hence with increased market share, the new capture cost decreases showing the impact of technology learning (Figure 1). The carbon tax is necessary to generate and sustain demand. The deterministic model shows the carbon tax remains the same (Figure 1). Initial cost of carbon capture is 55.4 ($/t), reducing to an optimal value of 27.8 ($/t) at 100% market share for the deterministic model (Figure 2). The reduction from increased demand is validated by the learning rate effect where cost reduces when technology providers accumulate experience.

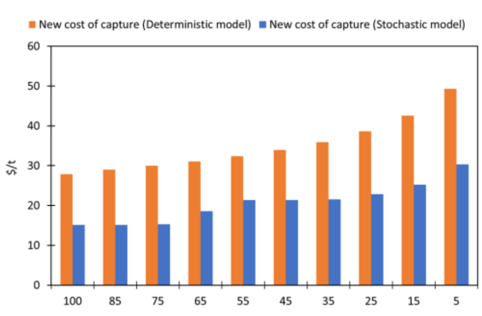

Fig. 2. New cost of capture for the stochastic and deterministic model

In the stochastic model in Eq. (12) and Eq. (13), randomized parameters replace the fixed parameters in the deterministic model. 200 scenarios are generated with various market shares, an optimal objective value and associated policy (carbon tax) are determined. Figure 1 shows the carbon tax required to achieve increased uptake of CCS; which is dependent on the demand pull. The carbon tax reduces the cost of capture and generates sufficient demand to sustain the cost reduction; hence the increase in the objective function (Figure 1). At 100% market uptake, the cost of capture reduces by 72.7%, and the carbon tax is 102.6 $/t – only 9.3 $/t higher than the carbon tax at the lowest market share.

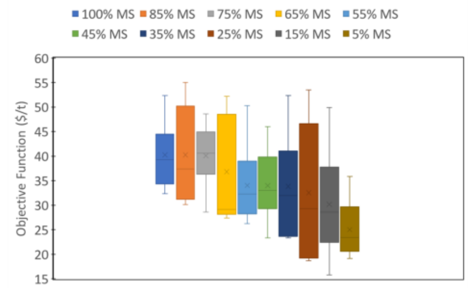

Fig. 3. Objective value spread for 200 scenarios. MS is market share

The new cost of capture is lower for the stochastic model (Figure 2) showing that considering uncertainty leads to better outcomes. A lower new cost of capture due to demand-pull from the carbon tax is obtained from the stochastic model. the new cost of capture is as low as 15.1 ($/t) at 100% market share for the stochastic model. Results also show that once the market share increases to 75%, it brings a significant cost reduction due to a carbon tax of 106.04 ($/t). Therefore, accounting for uncertainties in the learning rate and capture rate results in better decisions. The model applied 200 scenarios to represent a real circumstance with a random learning rate and a random capture rate. Then, for each scenario, the model provides one optimal value (Figure 3), one carbon tax (Figure 4) and new cost of capture (Figure 5) from a spread of value per market share. The distribution of the plants for selected market shares is shown in Figure 6 – 17 plants adopt CCS when the market share is 25% (carbon tax of 108.9 $/t) and 50% (Carbon tax of 111.3 $/t), and all plants adopt with a market share from 75% (resulting in carbon tax of 102.6 $/t at 100% market uptake). The value of the carbon tax also reduces as demand pull increases.

Whilst Stochastic programming is applied to integrate uncertainty in our optimisation model by solving the problem for the number of scenarios, setting

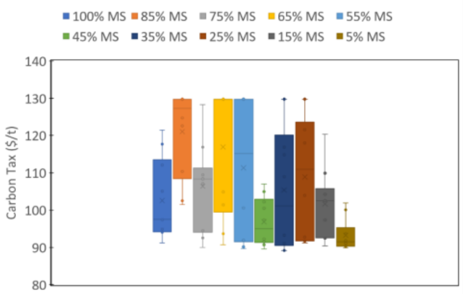

Fig. 4. Optimal carbon tax spread for 200 scenarios

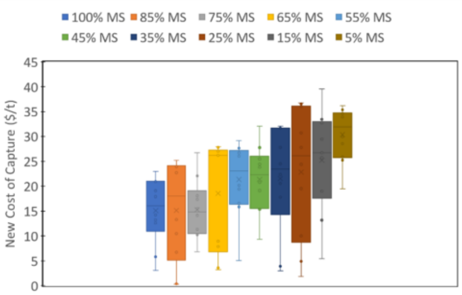

Fig. 5. Determined new capture cost for all market share for the 200 scenarios considered

the number of scenarios requires making a trade-off between problem representation issues and tractability issues. The problem might be intractable if the number of scenarios used to approximate it is too large. On the contrary, if only a few scenarios are used, then the problem would not be represented appropriately. In our work, the number of scenarios is determined by investigating the relation between the optimal objective value and the number of scenarios. To further increase the robustness, the future work can define the number of scenarios by using sample average approach method. This model capability is in quantifying the cost reduction potential from demand-pull created by market-based policy support, the macro-economic impacts of decarbonising the end use sector is not within scope.

4. CONCLUSIONS

This study developed and applied a novel Stochastic Market Potential Optimisation Model to quantify the impact of policy support (carbon tax) in reducing cost and generating sufficient demand for a clean technology (CCS) in 32 integrated steel plants in the EU to reduce capture cost under uncertainty. The objective of the optimisation model is to maximise the difference between the initial cost of capture and new cost of capture, where the latter is determined from increased demand (i.e., market share). This study also compares the results of the novel stochastic model with its deterministic counterpart. Sensitivity analysis shows the learning rate and carbon capture rate have the highest impact on the outcome. Hence, they are assumed to be normally distributed. Results obtained validate the impact of increased demand on cost reduction via learning effects due to having a carbon tax. Results also show the stochastic model's outcome is 34.2% better than the deterministic model for the same market share (market demand). A single policy (carbon tax) is investigated in our study, future work can apply the model to other policy support schemes. The model shows that the range of carbon tax to generate sufficient demand in CCS is between 93 ($/t) and 121 ($/t), significantly lower than the current carbon tax published among European countries. Which means more can be done with less taxes if the decision process is optimised.

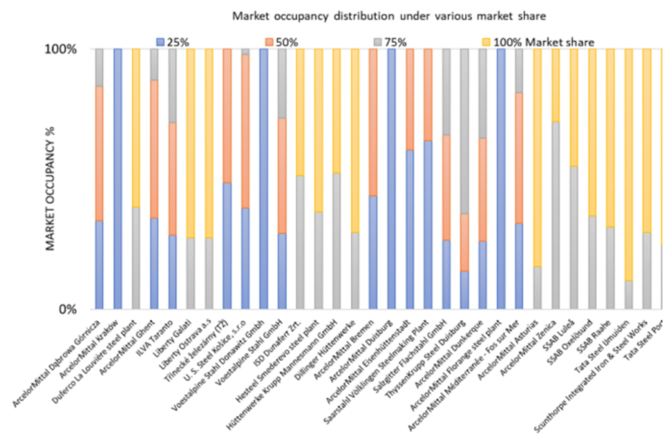

Fig. 6. Determined new capture cost for all market share for

DECLARATION OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. All authors read and approved the final manuscript.

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APPENDIX

Table A.1 Data set for all plants

Country	PLANT	CO_2 Emissions per plant (t/yr)	Cost at 63% Capture rate ($/yr)	CO2 emissions captured (t/yr)
Poland	ArcelorMittal Dąbrowa Górnicza	6,840,000	378,994,140	5,171,040
Poland	ArcelorMittal Kraków	1,862,000	103,170,627	1,407,672
Belgium	Duferco La Louvière steel plant	2,793,000	154,755,941	2,111,508
Belgium	ArcelorMittal Ghent	6,650,000	368,466,525	5,027,400
Italy	ILVA Taranto	8,170,000	452,687,445	6,176,520
Romania	Liberty Galati	3,990,000	221,079,915	3,016,440
Czech Republic	Liberty Ostrava a.s	3,990,000	221,079,915	3,016,440
Czech Republic	Třinecké železárny (TŽ)	4,765,200	264,032,584	3,602,491
Slovakia	U. S. Steel Košice, s.r.o	5,985,000	331,619,873	4,524,660
Austria	Voestalpine Stahl Donawitz Gmbh	1,995,000	110,539,958	1,508,220
Austria	Voestalpine Stahl GmbH	7,980,000	442,159,830	6,032,880
Hungary	ISD Dunaferr Zrt.	2,128,000	117,909,288	1,608,768
Serbia	Hesteel Smederevo steel plant	2,926,000	162,125,271	2,212,056
Germany	Hüttenwerke Krupp Mannesmann GmbH	2,090,000	115,803,765	1,580,040
Germany	Dillinger Hüttenwerke	3,724,000	206,341,254	2,815,344
Germany	ArcelorMittal Bremen	5,320,000	294,773,220	4,021,920
Germany	ArcelorMittal Duisburg	1,634,000	90,537,489	1,235,304
Germany	ArcelorMittal Eisenhüttenstadt	3,800,000	210,552,300	2,872,800
Germany	Saarstahl Völklingen Steelmaking Plant	3,591,000	198,971,924	2,714,796
Germany	Salzgitter Flachstahl GmbH	8,740,000	484,270,290	6,607,440
Germany	ThyssenKrupp Steel Duisburg	15,960,000	884,319,660	12,065,760
France	ArcelorMittal Dunkerque	8,911,000	493,745,144	6,736,716
France	ArcelorMittal Florange steel plant	4,256,000	235,818,576	3,217,536
France	ArcelorMittal Méditerranée - Fos sur Mer	7,049,000	390,574,517	5,329,044
Spain	ArcelorMittal Asturias	6,650,000	368,466,525	5,027,400