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Original Research Article

A Model for Equitable Allocation of Carbon Credits: The Case of the Cement Industry

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ABSTRACT

In response to the quest for net zero carbon emissions, many countries and regions have recently proposed new regulations that require corporations to disclose their greenhouse gas emissions. Corporate carbon damages (CCD) that account for a firm's actual emissions and profit can be a useful indicator. Companies and corporations, especially those that are in sectors that are inherently difficult to decarbonize, will have to rely on carbon credits to meet their emissions commitments. However, there is still a lack of adequate systematic methodology for the equitable allocation of available carbon credits to multiple corporations in a common market. To address this research gap, this work first proposes a new indicator called the net corporate carbon damage ($\mathrm{CCD}_j^{\mathrm{net}}$), which is the ratio of the net climate damage to net profit considering the effect of carbon credits and their cost on corporate performance. A mathematical model is then developed for the optimal and equitable allocation of available carbon credits by minimizing $\mathrm{CCD}_j^{\mathrm{net}}$ for a given set of corporations. The proposed model uses $\mathrm{CCD}_j^{\mathrm{net}}$ as its central metric, ensuring that the allocation balances carbon reduction and profitability while prioritizing the worst-performing companies to promote equity. Two case studies with contrasting levels of difficulty in decarbonizing are presented to demonstrate the capabilities of the model. Results suggest that achieving net zero emissions relies on a careful balance between available carbon credits, emissions reduction requirements, and company profitability. Companies with initially low CCD (between 0.0475 to 0.342) can achieve net zero emissions and equitable allocation. However, for difficult-to-decarbonize companies with higher CCD (between 2.61 to 15.77), net zero emissions and equitable allocation may not be possible even with external carbon credits. The model shows that equitable allocation is achievable when profit constraints are not binding; otherwise, a fundamental process technology change will be a better option.

KEYWORDS

Carbon footprint, Carbon budget, Greenhouse gas removal, Negative emissions technologies, Mathematical programming.

INTRODUCTION

The goal of limiting global warming to well below 2°C by the end of the 21st century requires achieving net zero greenhouse gas (GHG) emissions by mid-century. These targets require deep decarbonization of human activities to be achieved within a very short timeframe and a rapidly declining global carbon budget [1]. Many developed and emerging economies have set carbon neutrality pledges in support of this common climate change mitigation effort. Such policy targets provide the framework for implementing decarbonization measures in the agricultural, industrial, commercial, and residential sectors. The key approaches needed for decarbonization include energy efficiency enhancement, reduction of fossil fuel use in favor of renewables, CO_2 capture, utilization, and storage, and the generation of CO_2 removal (CDR) credits with nature-based or engineered techniques. While recent market trends have made low-carbon technologies such as renewables much more attractive from a cost-competitiveness standpoint [2], economic and policy instruments such as taxes, subsidies, or carbon trading will remain essential in providing stimulus for industrial decarbonization.

Road maps have been developed for the net zero pathway of sectors such as cement [3], chemical [4], iron and steel [5], and pulp and paper [6] industries. In addition, sector guidance to achieve net zero has also been developed [7]. For any given sector, reaching net zero will require the massive scale-up [8] and development of decarbonization portfolios [9] which also need to be aligned with country-specific conditions [6]. These measures should also account for the heterogeneity of emissions intensities within industrial sectors, even if the constituent companies produce similar goods using similar technologies [10]. The term "corporate carbon damages" (CCD) has been proposed as an indicator for measuring the social carbon cost of corporate emissions. CCD is defined as the ratio of the monetary equivalent of the entity's direct CO_2 emissions with its operating profit [10]. The direct emissions are converted to the monetary equivalent using the social cost of carbon (SCC), which is the external cost of the damage done by emitting an additional ton of greenhouse gas emissions. Corporations with low GHG intensities can provide useful performance benchmarks for laggard companies within the same sector. Greenstone et al. [10] also argued that mandatory disclosure of corporate GHG emissions along with financial data can help drive deep decarbonization.

Deep decarbonization of industrial sectors will incur costs from capital investments in required technologies or from the direct procurement of carbon credits. Various negative emissions technologies (NETs) can be used to generate CDR to offset GHG emissions if direct decarbonization is too costly to be implemented. NETs include different engineered (e.g., direct air capture or DAC) or nature-based (e.g., re- and afforestation) techniques that rely on different pathways to remove CO_2 from the atmosphere and transfer the CO_2 or carbon to another physical compartment. Recent analysis indicates that NETs exhibit a wide range of cost-effectiveness and storage permanence [11]. Extensive works have also been done to assess the overall environmental profile of NETs using life-cycle assessment and related tools [12]. In addition, decision-support models will be needed to rationalize the deployment of NETs for large-scale decarbonization [13]. Models can aid the rational deployment of NETs for optimal decarbonization [14].

The heterogeneity of corporate GHG intensities within industry sectors raises the question of how to properly allocate decarbonization obligations. The allocation of responsibility should also account for the financial performance of cooperation and the cost of available decarbonization measures. Equitable allocation of carbon credits is crucial in various systems, including distribution between corporate units. Equitable allocation ensures that each entity's share of the carbon budget is proportional to its emissions and financial capacity, promoting fairness and encouraging collective action towards decarbonization. Equitable allocation can be based on the ratio of corporate GHG emissions to profitability after the implementation of decarbonization measures; this intensity figure should be benchmarked with the SCC. Rennert et al. [15] estimate SCC at USD 185/t CO_2. Ratio-based allocation of decarbonization responsibility ensures equity since it simultaneously considers accountability (i.e., baseline emissions) and capacity (i.e., profit). Despite the extensive literature on industrial decarbonization, there remains a clear research gap in the absence of any decision-support models to rationalize the allocation of decarbonization obligations based on this principle.

To address this research gap, a novel mathematical programming model is developed in this work for optimizing the allocation of carbon credits among a group of companies within the same industrial sector. This work focuses on the cement industry as a representative sector. The credits are allocated equitably based on the baseline profitability and carbon intensity of the companies involved. The allocation is based on the principle that it is reasonable to expect similar companies within the same sector to have comparable carbon intensity per unit of profit. Thus, the carbon credits should be allocated to smooth out any observed heterogeneity within a sector [10]. Unlike the previous models, the current proposed model integrates both environmental (emissions) and financial (profitability) performance into a single metric, ensuring a more holistic approach to decarbonization.

The rest of this paper is organized as follows. The next section provides a literature review on the challenges faced by the cement industry in relation to decarbonization. It is then followed by the methodology section which presents the formal problem statement, the formulation of the mathematical optimization model, and the description of the case studies. The following sections then present the results of these case studies and their general implications for industrial decarbonization. Finally, the conclusions and promising directions for future research are discussed.

LITERATURE REVIEW

The cement industry accounts for 7% of global CO_2 emissions and needs deep decarbonization to allow net zero targets to be met [16]. In 2022, global cement production emitted 2,418 Mt CO_2 [17]. To achieve net zero, the industry must reduce its CO_2 emissions by at least 2.9% each year by 2030, followed by a more aggressive reduction rate of 12% each year by 2050 [18]. However, the current decarbonization performance falls short of the required reduction trajectory.

Reaching net zero CO_2 emissions in the cement sector is challenging due to the inherently high carbon intensity of production and limited readiness of alternative technologies. Most of the CO_2 emissions in the sector come from process heating [19] and the basic process chemistry itself [20]. Measures to reduce these emissions include incremental energy improvements, fuel switching, clinker substitution, and carbon capture and storage (CCS). Without widespread adoption of these technologies, CO_2 emissions are likely to increase [1] especially as demand for cement also grows [21].

Researchers in different countries have explored various strategies to address this problem. Huang and Wu [22] discovered that improving combustion systems, modernizing clinker coolers, optimizing process control, and using waste heat recovery for power generation can significantly reduce CO_2 emissions during clinker production. They also found that using adjustable speed drives for fans used in various production processes shows promising decarbonization potential. Talaei et al. [23] highlighted that grinding cement with materials like slag, fly ash, or volcanic ash can lower energy use and carbon emissions. They also noted that upgrading older kilns with suspension preheaters and improving clinker production refractories can result in energy savings of 4 kWh/t of cement and 0.06 GJ/t of clinker, respectively. Zhang et al. [24] reported significant CO_2 reductions in cement plants adopting high-efficiency classifiers and roller mills, multi-stage preheater kilns, and homogenizing raw mill blending systems.

Most cement plants still heavily rely on fossil fuels, but they can cut energy-related CO_2 emissions by using alternative fuels. IEA [18] aims to increase low-emissions fuel share in cement production by up to 30% by 2030 and 86% by 2050, primarily with biofuels combined with carbon capture, utilization, and storage [25]. In the European Union, 16% of the energy mix was successfully co-generated by biomass [26]. Co-firing with waste tires [27] and municipal waste

[28] has also been reported. The use of waste-derived fuel not only reduced emissions but also lowered the cost of clinker production. Green hydrogen is also now emerging as a clean fuel source for deeper carbon reductions [29]. CO_2 emissions from clinker production can be reduced by replacing raw materials with low-carbon alternatives [19], as well as improving existing equipment with more energy efficient technologies. Various alternative clinkers have also been studied as a means of reducing carbon footprint relative to Portland cement clinker [30]. The possibility of transitioning clinker production from fossil fuel-based to electric-based has also been investigated [31]. Eco-friendly calcareous oil shale as cement clinker replacement has been studied [32].

CCS offers a means to clean up emissions generated during cement production. De Lena et al. [33] integrated a calcium looping process with a single oxyfuel calciner to reduce CO_2 emissions by 93.4%. Liu et al. [34] reported that an electrified calcium looping process with thermal energy storage captured 90% of CO_2 emissions. Another configuration of calcium looping powered by solar energy also achieved a similar 90% CO_2 reduction [35]. Other CCS methods include pre-combustion CCS through gas-liquid absorption [36] and hydrate-based CCS [37]. Oxyfuel combustion provided around 92% carbon reduction [38]. Zajac et al. [39] applied CO_2 mineralization to capture CO_2 from power plants and cement kilns and used them for concrete carbonation. Deployment of these technologies will be crucial for deep decarbonization to meet climate targets by 2050 [40].

Even after the application of these decarbonization technologies, residual CO_2 still needs to be dealt with to reach net zero. This can be done through atmospheric CDR using NETs [1]. Bioenergy with CCS (BECCS) and direct air carbon capture (DAC) are the most mature types of engineered NETs [41]. Huang et al. [42] estimate the CDR potential of BECCS at up to 0.95 Gt CO_2/y. Many DAC demonstration plants and start-ups have been established throughout the world, but both technological maturity and scale still need to be improved [43]. Nature-based NETs also offer alternative means of generating CDR. Enhanced weathering of alkaline rocks and minerals can capture CO_2 via accelerated geochemical reactions [44]. Photosynthesis can also be leveraged for CDR using pathways such as biochar application [45], blue carbon management [46] also known as ocean afforestation [47], wetland [48] or mangrove restoration [49], and terrestrial afforestation [24]. However, most of these techniques result in CDR with low durability or permanence and have relatively limited climate change mitigation value [50].

There is extensive literature on technologies to decarbonize the cement industry, but options for deep decarbonization for an eventual net-zero state are not yet mature. In summary, studies have shown that optimizing combustion systems, upgrading kilns, and adopting energy-efficient technologies can significantly reduce CO_2 emissions during cement production. Additionally, the use of alternative fuels such as biofuels, waste-derived fuels, and green hydrogen, as well as low-carbon clinker substitutes, has shown promise in reducing emissions. Innovations in CCS, including calcium looping, oxyfuel combustion, and CO_2 mineralization, have achieved impressive emissions reductions. Furthermore, carbon dioxide removal (CDR) methods, such as BECCS, DAC, and nature-based solutions like enhanced weathering and afforestation, offer pathways to offset residual emissions. Hard-to-abate emissions from this sector will thus need to be offset through the calibrated use of carbon credits. Equitably allocating carbon credits can enhance this approach by ensuring that credits are distributed fairly based on the environmental and financial performance of companies.

Developing a decision-support model to rationalize the allocation of decarbonization obligations involves several challenges, primarily due to the need to balance multiple competing objectives and constraints. Equity may conflict with cost-effectiveness, as companies with higher emissions and lower profits may require more credits, potentially increasing overall costs. Complex constraints that consider carbon credit supply limits, minimum profit requirements, target carbon emissions reduction add to the complexity in solving the model. Companies within the same sector often have varying emissions intensities, profit margins, and capacities to adopt decarbonization measures. The model must account for this heterogeneity to ensure that allocations are both equitable and practical.

METHODOLOGY

This section presents the formal problem statement, model formulation, and a description of the case studies used to demonstrate the model.

Formal problem statement

The problem is represented schematically in **Figure 1** and may be formally stated as follows.

- Given a set of carbon credit sources $i \in I$ (i=1, 2, 3,…, I) and a set of carbon credit sinks $j \in J$ (j=1, 2, 3,…,J). The sinks may be represented by companies needing carbon emission reductions.
- Each carbon credit source i is depicted by its unit cost (Q_i) and supply limit (S_i).
- Each carbon credit sink j is depicted by its total emissions (E_j), profit (P_j), target carbon offset as a percentage (b_j) of its baseline emissions, and target minimum profit as a percentage (a_j) of its baseline profit. The target carbon offset of each sink may be set internally based on cascading policies from the national level.
- The external carbon credit allocation from source i to sink j is represented by x_{ij}.
- Given the prevailing social cost of carbon (SCC).

In this work, we propose the term "net corporate carbon damage" (CCD_j^{net}) as the ratio of the net climate damage and net profit. The net climate damage of each sink j is determined by its total emissions minus the sum of its carbon credits from the various sources. This quantity is converted to a monetary equivalent by multiplying with the social cost of carbon. On the other hand, the net profit of each sink j is determined by its total profit minus the sum of its carbon credit cost from various sources i.

The problem is to find the optimal allocation of the fixed external carbon credits to the set of sinks by minimizing CCD_j^{net} of the worst-performing sink in the system while meeting the target carbon offset and target minimum profit of each sink. This way, the carbon credit purchasing responsibility accounts for both the emissions and financial performance of companies, promoting equity. It is assumed that the net emission of each sink cannot be negative since there is no added value for each sink to be net negative emissions. It is also assumed that the net profit of each sink cannot be negative (a_j cannot be zero) to maintain profitability. The source-sink superstructure of the model is illustrated in **Figure 1**.

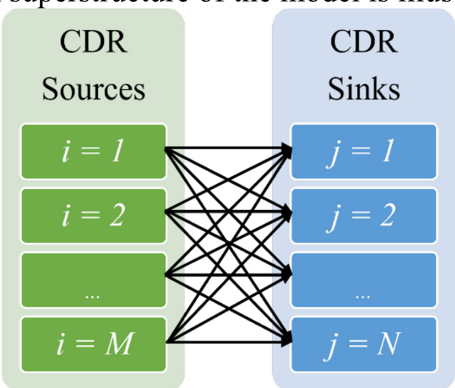

Figure 1. Source-sink superstructure for the carbon credit allocation network

Model formulation

As first defined by Greenstone et al. [10], industry j's corporate carbon damage, CCD_j is the ratio of the product of its CO_2 equivalent direct emissions, E_j, and the social cost of carbon, SCC, with its operating profit or sales, P_j, depicted in (Eq.(1)). This metric quantifies the environmental impact of a firm relative to its financial performance. Our proposed indicator, "net corporate carbon damage" (CCD_j^{net}), accounts for the impact of acquiring carbon credits on an industry's environmental performance. This new indicator is defined as the net climate damage to the net profit ratio (Eq.(1)). In contrast to the original indicator proposed by Greenstone et al. [10], CCD_j^{net} now incorporates carbon credits (x_{ij}) and their costs (unit cost Q_i multiplied with x_{ij}). It is desirable to minimize this ratio since it will indicate a reduction in the net climate damage and/or an increase in the net profit of the sink (e.g. industry or company):

$$CCD_j = \frac{E_j \times SCC}{P_j} \tag{1}$$

$$CCD_j^{net} = \frac{\text{Net Climate Damage}_j}{\text{Net Profit}_j} = \frac{(E_j - \sum_i x_{ij}) \times SCC}{\left(P_j - \sum_i Q_i x_{ij}\right)} \tag{2}$$

Eqs. (3) to (8) give the optimization model described by the problem. The objective function in Eq.(3) minimizes the CCD_j^{net} of the worst-performing sink, represented by δ. This ensures that the allocation of carbon credits improves the performance of the most disadvantaged firm, promoting equity across the sector. The objective function is subject to Eq.(4), which expresses the relationship of the net climate damage to the net profit in terms of δ. It ensures that the net climate damage for each firm *j* does not exceed δ times its net profit, linking environmental and financial performance.

$$\text{minimize } \delta \tag{3}$$

$$(E_j - \sum_i x_{ij}) \times SCC \leq \delta \times \left(P_j - \sum_i Q_i x_{ij}\right) \quad \forall j \tag{4}$$

Eq.(5) gives the carbon credit supply balance, ensuring that the total carbon credits allocated from each source i do not exceed its supply limit S_i. Eq.(6) is a constraint that ensures that the net profit meets a minimum value based on a percentage of the baseline profit, a_j. This guarantees that companies remain financially viable after purchasing carbon credits. Here it is assumed that a_j has a nonzero value, hence, the net profit will always be positive:

$$\sum_j x_{ij} \leq S_i \quad \forall i \tag{5}$$

$$P_j - \sum_i Q_i x_{ij} \geq a_j \times P_j \quad \forall j \tag{6}$$

Eq.(7) sets a target for carbon credit allocation, requiring that each firm *j* offsets at least a fraction b_j of its emissions E_j. This ensures the participation of each firm toward emissions reduction. The parameter b_j multiplied by the emissions (E_j) gives the target carbon offset for each sink j. Eq.(8) ensures that the net emissions depicted by the left-hand side of the equation have a non-negative value, preventing companies from achieving net-negative emissions, which is assumed to provide no additional benefit given that they are already dependent on purchased CDR. The parameter L in Eq.(8) is an arbitrarily low value. This assumes that there is no added value to companies to reach net negative emissions:

$$\sum_j x_{ij} \geq b_j \times E_j \quad \forall j \tag{7}$$

$$E_j - \sum_i x_{ij} \geq L \qquad \forall j \tag{8}$$

The proposed mathematical model addresses the challenges described in the review of literature by formulating the problem as a quadratic programming model with clear objective functions and constraints. By minimizing CCD_j^{net} and incorporating constraints such as supply limits, profit requirements, and emissions targets, the model provides a systematic framework for equitable and efficient carbon credit allocation. By focusing on the worst-performing sink, the model ensures that no firm is disproportionately burdened by the carbon credit allocation process. The combination of the constraints, **Eq.(4)** to **Eq.(8)** ensures that carbon credits are allocated in a way that balances environmental accountability (emissions reduction) with financial capacity (profitability). The model is demonstrated in two contrasting case studies, which are described in the next section.

Case Studies

Carbon credits are tradable certificates or permits that represent the right to emit a specified amount of CO_2. They are a key instrument in carbon markets, designed to incentivize emissions reductions by putting a price on carbon **[51]**. Carbon credits can originate from two main sources: (1) emissions reduction projects, such as renewable energy installations or energy efficiency improvements, and (2) CDR technologies, which actively remove CO_2 from the atmosphere. CDR technologies include nature-based solutions like reforestation and soil carbon sequestration, as well as engineered approaches such as DAC and BECCS **[1]**.

Two case studies with contrasting levels of difficulty in decarbonizing are used to demonstrate the capabilities of the model. Case Study 1 uses hypothetical data for both CDR sources and sinks, while Case Study 2 uses actual sink data from the cement industry and hypothetical data for the CDR sources. In this study, carbon credits are assumed to come from CDR technologies, which are the sources in the model.

Case study 1. The first case study is an illustrative case that consists of three carbon credit sources and eight carbon credit sinks. Although the scenario is fictitious, the case represents industries with a low baseline CCD_j. **Table 1** shows the data for the sinks, including their profits and emissions. An SCC value of 190 USD/t is assumed based on the US Environmental Protection Agency (US EPA) value **[10]**. Climate damage is calculated by multiplying the emissions (E_j) by the SCC (see column 4 of **Table 1**).

Table 1. Case Study 1 data for sinks

CDR Sink	Profit, P_j (M USD/y)	Emissions, E_j (Mt/y)	Climate Damage, $E_j \times$ SCC (M USD/y)
D1	50	0.0125	2.375
D2	30	0.012	2.28
D3	75	0.0375	7.125
D4	60	0.045	8.55
D5	50	0.045	8.55
D6	20	0.024	4.56
D7	200	0.25	47.5
D8	25	0.045	8.55
Total	510	0.471	89.49

On the other hand, **Table 2** shows the data for the carbon credit sources with their supply limits and unit costs. The unit costs of the CDR are based on the projected unit costs of terrestrial CDR technologies such as biochar, enhanced weathering, and direct carbon capture and storage in 2050 **[52]**. For simplicity, the minimum net profit is assumed to be 50% of the baseline profit (a_j=0.50) for all sinks. The minimum target CDR is assumed to be 5% of the baseline emissions (b_j=0.05) for all sinks.

Table 2. Case Study 1 data for sources

CDR Source	Supply, S_i (Mt/y)	Unit Cost, Q_i (USD/t)
S1	0.1	80
S2	0.3	120
S3	0.1	220
Total	0.5	

Case study 2. Case Study 2 uses published cement industry data [53] consisting of ten companies and four hypothetical CDR vendors. The capitalization and production data of the corporations are found in Table 3. The profits for each corporation are determined by assuming a capitalization-to-profit (P/E) ratio of 20. The emissions are determined by assuming an intensity of 0.6 t CO_2/t cement. The calculated climate damages in column 6 are much higher compared to Case Study 1. The data for the four CDR sources are shown in Table 4. For comparison, Case Study 2 uses the same parameter values for the SCC, target minimum percentages of profit (a_j), and CDR (b_j) as with Case Study 1.

Table 3. Case Study 2 data for sinks

Corporation	Capitalization (B USD)	Production (Mt/y)	Profit,P_j (M USD/y)	Emissions, E_j (Mt/y)	Climate Damage, $E_j \times SCC_j$ (M USD/y)
D1	3.4	15	170	9.0	1710
D2	7.7	21	385	12.6	2394
D3	5.3	14	265	8.4	1596
D4	9.4	20	470	12.0	2280
D5	34.8	233	1740	139.8	26562
D6	19.3	125	965	75.0	14250
D7	29.7	34	1485	20.4	3876
D8	4.7	23	235	13.8	2622
D9	17.0	48	850	28.8	5472
D10	12.6	67	630	40.2	7638
Total	143.9	600.0	7195.0	360.0	68400

Table 4. Case Study 2 data for sources

CDR Source	Supply, S_i (Mt/y)	Unit Cost, Q_i USD/t)
S1	20	120
S2	50	145
S3	80	160
S4	100	210
Total	250	

RESULTS

The solution to the case studies is obtained using the model described by Eqs. (3) to (8), which are implemented and executed using the software LINGO 19.0, which uses a deterministic global solver for nonlinear models [54]. The models are solved using a laptop with 16.00 GB RAM, AMD Ryzen 7 CPU, and a 64-bit operating system running on Windows 11 Pro. The runtime elapsed is less than 1 second for each run. These working models are available upon reasonable request addressed to the corresponding author. The results of the case studies illustrate how different cases of baseline CCD_j achieve contrasting results.

Case Study 1. **Table 1** and **Table 2** provide the data input to the model presented in **Eqs.(3)** to **(8)**. **Table 5** shows the resulting optimal allocation of carbon credits to each sink. Columns 5 to 9 are derived values after optimization, and their mathematical expressions are shown in row 1. The baseline CCD_j and optimal CCD_j^{net} for each sink are shown in the last two columns. The baseline CCD_j values range from 0.0475 to 0.342, which can be interpreted as the baseline climate damages being 4.75 to 34.2% of the profits. After optimization, the total CDR of each sink equals its baseline emissions (100% reduction), thus resulting in zero net climate damage. The resulting net profit ranges from 0.74 to 0.97 of the baselines, as shown in column 9, which are far higher than the minimum set target of a_j=0.50 and implies that this constraint is not binding. Sources 1 and 2 are completely used up, while source 3 (the most expensive CDR) still has a remaining supply. All the sinks have a resulting CCD_j^{net} of 0, which is a decrease from their baselines. Hence, the value of δ or the ratio of the worst-performing sink is 0.

Figure 2 represents the Case Study 1 results where the sinks are arranged in increasing baseline emissions. In the equitable allocation, the assignment of CDR should consider the varied baseline values of both emissions and profits. For Case Study 1, equitable allocation can be observed in two ways. First, the total CDR as a fraction of the baseline emissions increases with increasing baseline emissions (see **Figure 2**), which means that the higher the corporation's baseline emissions, the higher the CDR is expected from that corporation. Second, the baseline CCD_j has an opposite trend, with net profit as a fraction of the baseline (see **Figure 2**), which implies that the higher the corporation's baseline CCD_j value, the higher the corporation is expected to spend on CDR with respect to its baseline profit.

Case Study 2

Using the data listed in **Table 3** and **Table 4** and the model described by **Eqs.(3)** to **(8)**, the resulting optimal carbon credit allocation and ratios for Case Study 2 are presented in **Table 6**. Compared to Case Study 1, the baseline CCD_j values of the current case are higher, ranging from 2.61 to 14.77. This indicates that the baseline climate damages are 261 to 1577% of the profits, which is expected of cement industries. The total CDR of each corporation meets the 5% target as shown in column 7. The corporations implement a reduction of 5 to 23% of their baseline emissions, in contrast with the previous case study, which implements a 100% reduction for all sinks. The net profit meets the 50% minimum target as shown in column 10, with a value of 0.5 for nine out of ten corporations. This implies that the constraint $a_j = 0.50$ is binding. The CDR cost in the current scenario has a significant impact on the profits of the sinks. As a result, the available carbon credits are not fully utilized. The optimum CCD_j^{net} are all higher than their baseline values, indicating that despite the reductions in climate damages, the reductions in profits are higher. The highest δ value is 28 from corporations D5 and D6, making them the worst-performing sinks. Note that sinks D5 and D6 are also the top two emitters of carbon dioxide based on **Table 3**. The two case studies reflect the heterogeneity of corporate carbon damages within industry sectors.

Case Study 2 results are arranged in increasing baseline profits as shown in **Figure 3**. Here, no trends are observed in the total CDR as a fraction of the baseline emissions. The optimum CCD_j^{net} follows the trend of the baseline CCD_j. Here, equitable allocation is not demonstrated, and all corporations are bound to the 50% net profit constraint.

Table 5. Results of Case Study 1

		Source i			Total CDR, $\sum_j x_{ij}$ (Mt/y)	Total CDR*	Net Climate Damage **	Net Profit ***	Net Profit as a Fraction of the Baseline****	Ratio	
		S1	S2	S3						Baseline, CCD_j	Optimum, CCD_j^{net}
Sink j	D1	0	0.0125	0	0.0125	1	0	48.50	0.97	0.048	0
	D2	0.012	0	0	0.012	1	0	29.04	0.97	0.076	0
	D3	0.032	0.003	0.002	0.037	1	s0	71.53	0.95	0.095	0
	D4	0	0.011	0.034	0.045	1	0	51.25	0.85	0.143	0
	D5	0.031	0.003	0.011	0.045	1	0	44.74	0.89	0.171	0
	D6	0	0	0.024	0.024	1	0	14.72	0.74	0.228	0
	D7	0	0.25	0	0.25	1	0	170.00	0.85	0.238	0
	D8	0.0250	0.02	0	0.045	1	0	20.61	0.82	0.342	0
	Total	0.1	0.3	0.071	0.471	1	0	450.38	0.88	0.180	0

* as a Fraction of the Baseline Emissions, $\sum_j x_{ij} / E_j$; ** $(E_j - \sum_i x_{ij})\times SCC$, (M USD/y); *** , $\left(P_j - \sum_i Q_i x_{ij}\right)$, (M USD/y)
**** $\left(P_j - \sum_i Q_i x_{ij}\right)/P_j$

Table 6. Results of Case Study 2

Sink j	S1	S2	S3	S4	Total CDR, $\sum_j x_{ij}$ (Mt/y)	Total CDR*	Net Climate Damage **	Net Profit***	Net Profit as a Fraction of the Baseline ****	Ratio: Baseline, CCD_j	Ratio: Optimum, CCD_j^{net}
	Source *i*										
D1	0.535	0.143	0	0	0.678	0.08	1581	85	0.50	10.06	18.60
D2	0	1.235	0	0.064	1.299	0.10	2147	193	0.50	6.22	11.15
D3	0.924	0	0.135	0	1.059	0.13	1395	133	0.50	6.02	10.53
D4	0	1.235	0.35	0	1.585	0.13	1979	235	0.50	4.85	8.42
D5	6.99	0	0	0	6.99	0.05	25234	901	0.52	15.27	28.00
D6	2.63	0.875	0.241	0	3.746	0.05	13538	483	0.50	14.77	28.00
D7	0.889	1.235	1.235	1.235	4.594	0.23	3003	743	0.50	2.61	4.04
D8	0.979	0	0	0	0.979	0.07	2436	118	0.50	11.16	20.73
D9	0.625	1.01	0	0.969	2.604	0.09	4977	425	0.50	6.44	11.71
D10	0	1.233	0.851	0	2.084	0.05	7242	315	0.50	12.12	22.99
Total	13.58	6.966	2.812	2.268	25.626	0.07	63532	3630	0.50	9.51	17.50

* as a Fraction of the Baseline Emissions, $\sum_j x_{ij} / E_j$; , $(E_j - \sum_i x_{ij}) \times SCC$ (M USD/y), Baseline, CCD_j; *** , $\left(P_j - \sum_i Q_i x_{ij}\right)$ (M USD/y)
**** , $\left(P_j - \sum_i Q_i x_{ij}\right) / P_j$

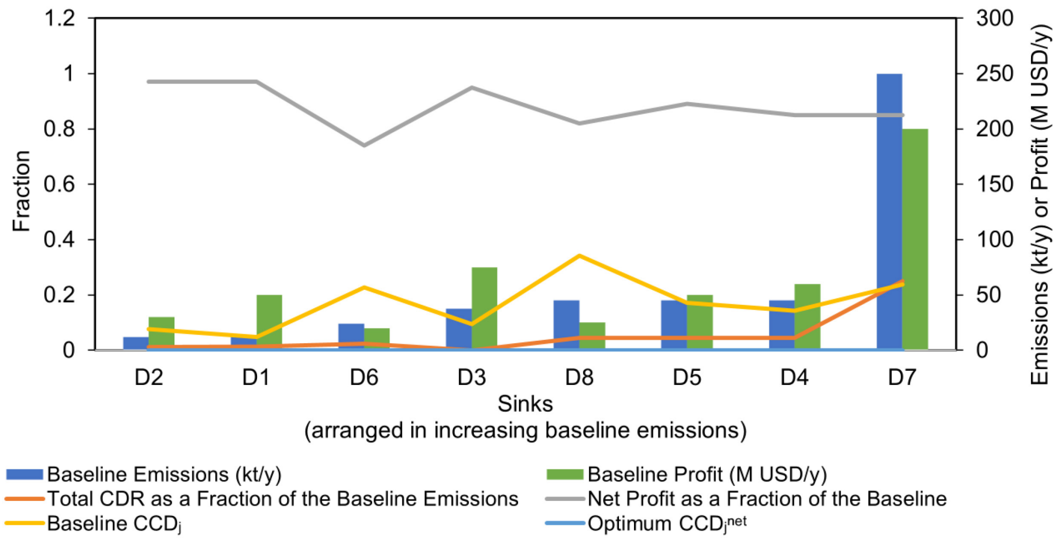

Figure 2. Case Study 1 results arranged in increasing baseline emissions (note: the baseline emissions are expressed in kt/y to fit the axis)

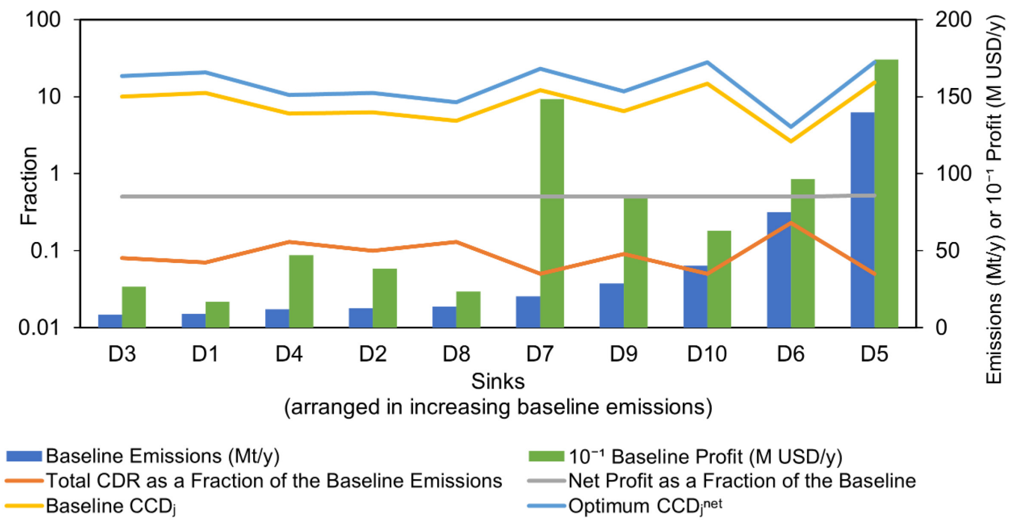

Figure 3. Case Study 2 results arranged in increasing baseline emissions (note: the baseline profits are expressed in 10^{-1} M USD/y to fit the axis)

Sensitivity Analysis

The sensitivity analysis is used to investigate the impact of varying the social cost of carbon (SCC) on the model's outcomes, including total CDR, net climate damage, and net profit. The SCC values tested include USD 50/t, USD 190/t (baseline value used in the case studies), USD 250/t, and USD 400/t. The results for Case Study 1 and Case Study 2 are presented in **Tables 7** and **8**, respectively.

Table 7. SCC Sensitivity analysis of Case Study 1

SCC, (USD/t)	Total CDR, (Mt/y)	Total CDR as a Fraction of the Baseline Emissions	Net Climate Damage, (M USD/y)	Net Profit, (M USD/y)	Net Profit as a Fraction of the Baseline
50	0.471	1	0	450.38	0.8831
190	0.471	1	0	450.38	0.8831
250	0.471	1	0	450.28	0.8829
400	0.471	1	0	450.38	0.8831

Table 8. SCC Sensitivity analysis of Case Study 2

SCC, (USD/t)	Total CDR, (Mt/y)	Total CDR as a Fraction of the Baseline Emissions	Net Climate Damage, (M USD/y)	Net Profit, (M USD/y)	Net Profit as a Fraction of the Baseline
50	25.394	0.0705	63575	3630	0.50
190	25.626	0.0712	63532	3630	0.50
250	25.401	0.0706	63574	3630	0.50
400	25.394	0.0705	63575	3630	0.50

For all SCC values tested using Case Study 1 data, the total CDR remains constant at 0.471 Mt/y, which corresponds to 100% of the baseline emissions. This indicates that the model achieves complete emissions offset regardless of the SCC value. Consequently, the net climate damage is zero across all scenarios, as the emissions are fully offset by the allocated carbon credits. The net profit remains stable at approximately USD 450.38 M/y, representing about 88% of the baseline profit. This consistency across SCC values suggests that the profit constraint (**Eq. (6)**) is not binding in Case Study 1, and the allocation of carbon credits does not significantly impact profitability.

In contrast to Case Study 1, the total CDR in Case Study 2 varies slightly with the SCC, ranging from 25.394 Mt/y (at USD 50/t and 400/t) to 25.626 Mt/y (at USD 190/t). However, these variations are minimal, and the total CDR remains around 7% of the baseline emissions. The net profit remains constant at USD 3,630 M/y, which is 50% of the baseline profit. This result indicates that the profit constraint (**Eq. (6)**) is binding in Case Study 2, limiting the ability to allocate additional carbon credits despite changes in the SCC.

The results show that the SCC has a limited impact on the total CDR and net profit in both case studies. This suggests that the model's allocation decisions are primarily driven by the constraints (profit targets and emissions reduction requirements) rather than the SCC value.

DISCUSSION

The two case studies demonstrate the potential of the mathematical model in identifying the optimal allocation of carbon credits among industries in a given sector. The results show that achieving CDR targets using carbon credits will depend on a delicate balance between the current performance of an industry (with respect to direct carbon emissions and profits), emissions reduction requirements, and profitability. These results have general implications beyond the specific instances described in the previous sections.

If current carbon emissions are relatively low, or if available credits are relatively cheap, then it is possible to reduce corporate carbon damages to zero as illustrated in Case Study 1. The first case study also demonstrates equitable allocation by considering the varied baseline emissions and profits in CDR allocation. However, for sectors that are difficult to decarbonize, reaching net zero may not be feasible even when enough carbon credits are available as illustrated in Case Study 2, especially if exceeded carbon emissions are taxed. Equitable allocation is difficult to achieve in such cases. Hence, for carbon-intensive industries, a technology change rather than buying carbon credits may be a better option. For example, this may entail a marked shift to renewables for power generation or the use of green hydrogen for heating in iron and steel production. Nonetheless, the $\mathrm{CCD}_j^{\mathrm{net}}$ remains useful as it indicates the potential for carbon emission reduction and can be used as a benchmark for industries in a given sector.

Another challenge is quantifying SCC so that it accurately reflects the damages of GHG emissions. The willingness of companies (and ultimately the general public) to pay for decarbonization efforts hinges on making this externality an actual financial cost for polluters. This will play a critical role in the mitigation of the damage brought by emissions. Governments are looking at various instruments, such as carbon taxes and carbon markets to further stimulate decarbonization in industry. However, trading requires the availability of surplus credits either from over-performing companies or from companies whose core business model is based on generating CDR using NETs. As noted by Greenstone et al. **[16]**, the availability of GHG emissions disclosures is also vital.

The sensitivity analysis showcases the model's ability to balance equity and feasibility. In Case Study 1, the model achieves equitable allocation with minimal trade-offs, while in Case Study 2, the binding profit constraint reflects the challenges faced by difficult-to-decarbonize industries. The sensitivity analysis also demonstrates the robustness of the model across a range of SCC values. While the SCC has minimal direct impact on the allocation outcomes, the results emphasize the critical role of profit constraints in determining the feasibility of decarbonization.

CDR is going to be an essential component of industrial decarbonization towards net zero goals to preserve the rapidly declining global carbon budget **[55]**. However, there are differences in the durability of CDR credits generated by different NETs, with nature-based options being particularly vulnerable to leakage or catastrophic reversal **[50]**. The predominance of nature-based NETs in current voluntary carbon markets has raised concerns about the long-term efficacy and credibility of CDR for deep decarbonization **[56]**. New frameworks thus need to be developed to quantify climate change mitigation value per unit of nominal CDR **[57]**. Such methods can be integrated into future variants of the model developed here.

CONCLUSIONS

This work proposes a new indicator, the net corporate carbon damage (CCD_j^{net}), which is the ratio between the net climate damage and the net profit of a firm, considering the purchase of carbon credits. A mathematical model is then developed to optimize the allocation of a limited supply of carbon credits to corporations within the same industry by minimizing the worst-performing net corporate carbon damage. The model uses the principle that similar or comparable carbon intensities can be expected within an economic sector, where companies use similar technologies to generate the same class of goods. These developments address the research gap of how to deal with the heterogeneity of corporate carbon damages within industry sectors by fairly allocating the purchase of carbon credits. Equitable allocation of carbon credits is achieved by minimizing the CCD_j^{net} of the worst-performing sink, ensuring no firm is disproportionately burdened while balancing environmental accountability and financial capacity. The two case studies demonstrate that for an industry with a relatively low baseline CCD_j (0.0475 to 0.342), the corporations can achieve net zero emissions and therefore, zero out their corporate carbon damages (Case Study 1). Here, the profit constraint is not binding, and an equitable allocation is observed. In contrast, for a difficult-to-decarbonize industry, such as the cement industry where the baseline CCD_j ranges from 2.61 to 15.77, the purchase of carbon credits may result in an increase in their net corporate carbon damages (Case Study 2). One reason is the considerable impact of buying carbon credits on their net profits. Unused carbon credits are left in Case Study 2 because the corporations are bound by the profit constraint to maintain profitability. Equitable allocation is not achieved in this scenario. These results imply that in cases where carbon damages are relatively large compared to corporate profit, decarbonization needs to be achieved through a fundamental change in process technology. The sensitivity analysis highlights the importance of financial viability in achieving decarbonization goals, particularly for industries with higher emissions and lower profit margins.

The model developed in this work offers the capability to support industrial decarbonization decisions by distributing carbon credits in an equitable manner, thus facilitating the transition towards net zero emissions. Future work can focus on applying this model and its underlying principles to a broader range of industrial sectors. Model extensions should also be developed to account for portfolios of decarbonization strategies, including technological shifts. Variations in the quality or durability of credits sourced from CDR should be considered. Temporal and geographic aspects can also be covered in multi-objective or game-theoretic versions of the original model.

DECLARATION ON USE OF AI TOOLS

Grammarly was used to aid in language polishing of this paper.

NOMENCLATURE

Sets

I	CDR sources
J	CDR sinks

Indexes

i	CDR source index
j	CDR sink index

Parameters

$\mathbf{a}_j$	Percentage of the baseline profit for each sink j	[%]
$\mathbf{b}_j$	Percentage of the baseline emissions for each sink j	[%]
$\mathbf{CCD}_j$	Carbon corporate damage performance of sink j	[M USD/y]
$\mathbf{E}_j$	Emissions of sink j	[Mt/y]
L	Arbitrarily low number	[dimensionless]
$\mathbf{P}_j$	Profit of sink j	[M USD/y]
$\mathbf{Q}_i$	Unit cost of CDR source i	[USD/t]
SCC	Social cost of carbon	[USD/t]
$\mathbf{S}_i$	Supply limit of CDR source i	[Mt/y]

Variables

δ	Worst $\mathbf{CCD}_j^{\mathbf{net}}$	[dimensionless]
$\mathbf{CCD}_j^{\mathbf{net}}$	Net carbon corporate damage performance of sink j	[dimensionless]
$\mathbf{x}_{ij}$	Carbon credit allocation from source i to sink j	[Mt/y]

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