CHEMICAL ENGINEERING TRANSACTIONS

VOL. 120, 2025

A publication of AIDIC
The Italian Association
of Chemical Engineering
Online at www.cetjournal.it

Guest Editors: Bing Shen How, Viknesh Andiappan, Denny K.S. Ng, Hon Loong Lam, Petar S. Varbanov

ISBN 979-12-81206-21-2; **ISSN** 2283-9216

DOI: 10.3303/CET25120064

Optimization Model for Progressive Industrial Decarbonization

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Many companies are setting corporate net zero emissions targets in response to the pressure of decarbonization trends. In industries that have hard-to-abate emissions, the options available for deep emissions cuts are limited to changing the fundamental process technologies, using carbon capture and storage (CCS), or purchasing carbon dioxide removal (CDR) credits. Investment decisions need to be carefully planned due to inherent techno-economic risks. In this work, a mixed-integer linear programming (MILP) model is developed for optimizing progressive industrial decarbonization plans. For a given system of multiple plants with specified baseline emissions, the model can be used to determine the cost-optimal timing of CCS retrofits to meet a series of interim emissions caps leading to an eventual net zero state; it is assumed that CDR credits can also be purchased at any time to offset any residual emissions from the system. The model is applied to two representative case studies to demonstrate how it can be used to support decision-making.

1. Introduction

Deep decarbonization of industrial sectors will be necessary to achieve global net zero aspirations. There is intensive research on different enabling technologies, such as process heat electrification and CO_2 capture, utilization and storage (CCUS), for making deep emissions cuts (Gailani et al., 2024). Sector-specific decarbonization roadmaps have been proposed for the carbon-intensive industries such as cement (Nehdi et al., 2024), chemicals (Thakker and Bakshi, 2024), iron and steel (Keramidas et al., 2024), and pulp and paper (Dai et al., 2024) production. However, the wide range of available options coupled with uncertainties inherent in new technologies complicates decision-making in practice.

The development of tools to address current sustainability challenges is a priority area for researchers in the areas of process systems engineering (PSE) (Pistikopoulos et al., 2021) and process integration (PI) (Wang et al., 2022). Many optimization models have been proposed to support industrial decarbonization decisions (Tan et al., 2025). For example, Nair et al. (2023) developed an open-source software for optimizing industrial decarbonization using a suite of options including the purchase of externally sourced carbon dioxide removal (CDR) credits. Lee et al. (2025) developed a mixed-integer linear program (MILP) to optimize the electrification of industrial boilers. Migo-Sumagang et al. (2025) proposed a framework for optimizing the equitable allocation of CDR credits within an industrial sector, considering the financial capability of each company to pay for decarbonization. CCUS or CO_2 capture, and storage (CCS) are essential technology options for making deep cuts in industries with hard-to-abate emissions (Bains et al., 2017), as evidenced by their inclusion in optimized decarbonization portfolios for the cement (Obrist et al., 2021), iron and steel (Li et al., 2023), and pulp and paper (Obrist et al., 2022) sectors.

CCS/CCUS technologies can be used to drastically reduce emissions in power generation and industrial plants (Bains et al., 2017). The conventional benchmark is reduction of baseline emissions by 90 %, although “deep CCS” approaching 100 % reduction is possible in principle (Dods et al., 2021). Optimization models have been proposed to optimize planning of CCS/CCUS deployment. Tan et al. (2013) developed an early MILP model for planning CCS retrofit of power plants. More recent models cover a broader range of industrial CO_2 point sources as well as utilization and sequestration options (Prousalis et al., 2024). However, there is still a need for generic,

Paper Received: 15 May 2025; Revised: 17 July 2025 ; Accepted: 30 October 2025
Please cite this article as: Aviso K.B., Foo D.C.Y., Poplewski G., Tan R.R., 2025, Optimization Model for Progressive Industrial Decarbonization, Chemical Engineering Transactions, 120, 379-384 DOI:10.3303/CET25120064

computationally tractable models to plan the decarbonization of industrial facilities over extended time horizons; in addition, practical scenarios will often involve "check points" or interim emissions reduction targets.

To address this research gap, a novel MILP model is developed for progressive decarbonization of multiple industrial sites towards an ultimate net zero goal. A discrete time formulation is employed with the option to use CCS and CDR to meet interim and final emissions targets. The model is computationally tractable and can be used to develop practical industrial decarbonization roadmaps. The rest of the paper is organized as follows. Section 2 defines the formal problem statement. Section 3 describes the MILP model formulation. Section 4 demonstrates the model on a tutorial case study, while Section 5 applies it to the case of decarbonizing Poland's cement industry. Section 6 states the conclusions and future research directions.

2. Problem statement

The formal problem is given as follows:

- Given a set of industrial plants with known baseline annual emissions which need to be decarbonized within a specified time horizon;
- Given that the planning horizon is divided into intervals with each interval having an interim decarbonization target;
- Given that the industrial plants can be decarbonized primarily through retrofit with CCS technology with known capture rates and capture costs;
- Given that the decision to retrofit should be made within a given period of time represented by the earliest time that the technology is available to the latest time of retrofit to ensure economic viability of the investment;
- Given that each plant can also buy CDR credits or pay a penalty (carbon tax) if the emissions limit is exceeded.

The problem then is to find the optimal decarbonization schedule which will minimize the over-all costs for the plants in the system.

3. Model formulation

The overall objective is to minimize the total cost (Eq(1)) associated with reaching the CDR target. This consists of the costs incurred in each period *k* for capturing CO$_2$ ($\mathrm{CaptureCost}_k$), buying CDR credits ($\mathrm{CDRCost}_k$), or paying penalties due to excess CO$_2$ emissions ($\mathrm{PenaltyCost}_k$). The capture cost is further defined in Eq(2) where BE_i is the baseline emission of plant *i*, RR_i is the removal rate with values ranging from 0 to 1, Z_{ik} is a binary parameter which indicates if plant *i* is still operational in period *k* ($\mathrm{Z}_{ik} = 1$), C_i is the unit cost for capturing CO$_2$, and x_{ik} is a binary variable that indicates if the retrofit is implemented for plant i in period k ($\mathrm{x}_{ik} = 1$) or not ($\mathrm{x}_{ik} = 0$). Eq(3) defines the cost associated with the carbon credits where CDR_k is the unit cost for carbon credits where y_{ik} indicates the amount of carbon credits needed by plant *i* in period *k*.

$$\mathrm{TotalCost} = \sum_{\mathrm{k}} (\mathrm{CaptureCost}_k + \mathrm{CDRCost}_k + \mathrm{PenaltyCost}_k) \tag{1}$$

$$\mathrm{CaptureCost}_k = \sum_{\mathrm{i}} \mathrm{x}_{ik}\mathrm{C}_i\mathrm{BE}_i\mathrm{RR}_i\,\mathrm{Z}_{ik} \qquad \forall \mathrm{k} \tag{2}$$

$$\mathrm{CDRCost}_k = \sum_{\mathrm{i}} \mathrm{y}_{ik}\mathrm{CDR}_k \qquad \forall \mathrm{k} \tag{3}$$

Any excess CO$_2$ from the target set in period k $\left(\mathrm{E}_k^{\mathrm{CAP}}\right)$ incurs a penalty cost (Eq(4)), where e_k refers to the emissions in period *k* and P_k is the unit penalty cost. The remaining emissions in period k (e_k) is defined by Eq(5) and will depend on whether the capture technology retrofit is activated for plant *i* in period *k* and if CDR credits are bought by the company. The total CDR credits used by companies in any given period *k* should not exceed what is available $\left(\mathrm{CDR}_k^{\mathrm{cap}}\right)$ as indicated in Eq(6).

$$\mathrm{PenaltyCost}_k > \left(\mathrm{e}_k - \mathrm{E}_k^{\mathrm{CAP}}\right)\mathrm{P}_k \qquad \forall \mathrm{k} \tag{4}$$

$$e_k = \sum_i [BE_i Z_{ik}(1 - x_{ik}) + BE_i Z_{ik}(1 - RR_i)x_{ik} - y_{ik}] \qquad \forall k \qquad (5)$$

$$\sum_i y_{ik} \leq CDR_k^{CAP} \qquad \forall k \qquad (6)$$

Once the retrofit is implemented, it remains operational until the end of the planning period (Eq(7)). The retrofit should be activated at a time (t_i^{start}) that will make the retrofit economical (Eq(8)), while T^{max} is the end of the planning horizon. The retrofit should begin within defined earliest (TL_i) and latest (TU_i) times of activation (Eq(9) and Eq(10)) where b_i is a binary variable that indicates if a retrofit was implemented for plant *i* (Eq(11)) and M is an arbitrary big number. Eq(12) and Eq(13) indicate the binary variables.

$$x_{ik} \leq x_{ik+1} \qquad \forall i,k \qquad (7)$$

$$t_i^{start} = T^{max} - \sum_k x_{ik} + 1 \qquad \forall i \qquad (8)$$

$$t_i^{start} \geq b_i TL_i \qquad \forall i \qquad (9)$$

$$t_i^{start} \leq b_i TU_i \qquad \forall i \qquad (10)$$

$$\sum_k x_{ik} \leq Mb_i \qquad \forall i \qquad (11)$$

$$x_{ik} \in \{0,1\} \qquad \forall i,k \qquad (12)$$

$$b_i \in \{0,1\} \qquad \forall i \qquad (13)$$

This MILP model can be readily implemented and solved using branch-and-bound solvers embedded in spreadsheet applications such as Excel optimization software such as LINGO or GAMS.

4. Case Study 1

The first case study is a tutorial demonstration that considers four hypothetical industrial plants that intend to cut down their emissions. The detailed model files are available upon request. The planning horizon is for five periods, with each period consisting of 5 years. The relevant plant data is summarized in Table 1 while the temporal system–level data is shown in Table 2.

Table 1: Plant data for case study 1

	Units	Plant 1	Plant 2	Plant 3	Plant 4
Baseline emissions, BE_i	kt/y	400	100	600	200
Earliest retrofit, TL_i	period	2	1	1	1
Latest retrofit, TU_i	period	4	4	3	2
Removal rate, RR_i	%	95	90	90	90
Capture cost, C_i	US$/t	40	40	30	35

Solving Eq(1) subject to the constraints in Eq(2) to Eq(13) results in a total system cost of US$ 994.50 M, majority of which will be spent capturing the CO_2. The distribution of costs is shown in Figure 1. Emissions for periods 1 to 3 were below the emissions limit set for the respective periods while CDR credits were needed for periods 4 and 5. Plants 3 and 4 were retrofitted with carbon capture technology as early as period 1 while plant 1 was retrofitted in period 2 and plant 2 in period 4.

Table 2: Temporal system–level data for case study 1

	Units	Period 1	Period 2	Period 3	Period 4	Period 5
Emissions cap, $\mathrm{E}_k^{\mathrm{CAP}}$	kt/period	3,000	1,500	750	250	0
CDR credit cost, CDR_k	US$/t	200	150	120	100	80
Penalty cost, P_k	US$/t	80	100	120	150	200
CDR supply cap, $\mathrm{CDR}_k^{\mathrm{CAP}}$	kt/period	100	200	400	800	1,600

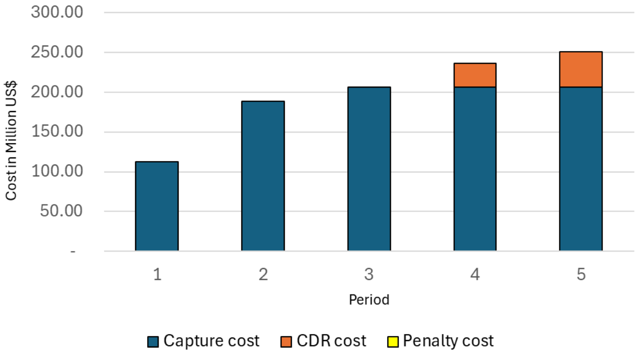

Figure 1. Cost distribution for optimal solution of case study 1

5. Case Study 2

The second case study considers industrial decarbonization in Poland. The detailed model files are also available upon request. As part of the European Union, Poland is committed to achieving carbon neutrality by 2050, with interim targets of 55 % emissions reduction by 2030 and 90 % by 2040. The country is facing challenges due to its high dependence on coal (Poplewski et al., 2025). Growth of non-fossil (renewables and nuclear) power generation and improved integration of the grid with neighbouring countries are expected to aid decarbonization efforts. This semi-hypothetical case study considers the decarbonization of 11 cement plants in Poland over a 25-year planning horizon (2025–2049) divided into 5-year intervals. The system data are shown in Tables 3 and 4. The annual CDR supply cap is also indicated in Table 4. Any retrofits must be in place at least 10 y before plant decommissioning or the end of the planning horizon.

Table 3: Plant data for case study 2

		Plant										
	Units	1	2	3	4	5	6	7	8	9	10	11
Baseline emissions, BE_i	Mt/y	5.11	2.40	2.00	2.20	0.80	1.60	2.50	0.60	0.45	0.06	5.00
Year of decommissioning		2047	2047	2034	2042	2026	2046	2044	2068	2030	2040	2046
Earliest retrofit, TL_i	kth year	1	1	1	1	1	1	1	1	1	1	1
Latest retrofit, TU_i	kth year	13	13	1	8	1	12	10	17	1	6	12
Removal rate, RR_i	%	90	90	95	90	95	90	95	95	95	90	95
Capture cost, C_i	US$/t	35	35	30	40	35	30	30	35	35	40	35

Table 4: Temporal system-level data for case

	Units	Period 1	Period 2	Period 3	Period 4	Period 5
Emissions cap, $\mathrm{E}_k^{\mathrm{CAP}}$	Mt/period	75	50	25	15	0
CDR credit cost, CDR_k	US$/t	200	150	120	100	80
Penalty cost, P_k	US$/t	80	100	120	150	200
CDR supply cap, $\mathrm{CDR}_k^{\mathrm{CAP}}$	kt/y	1,000	2,000	4,000	8,000	16,000

Solving Eq(1) yields a total cost of US$ 6.092 M. The cost distribution is illustrated in Figure 2. A penalty is paid from 2025–2029 while CDR credits are purchased in 2040 and 2041 as well as in 2045 to 2049. Only 5 plants were retrofitted for CCS, as shown in Table 5.

Table 5: Temporal system-level data for case

	Earliest	Latest	t_i^{start}	Decommissioning
Plant 1	2025	2037	2030	2047
Plant 2	2025	2037	2035	2047
Plant 3	2025	2025	No retrofit	2034
Plant 4	2025	2032	No retrofit	2042
Plant 5	2025	2025	No retrofit	2026
Plant 6	2025	2036	2035	2046
Plant 7	2025	2034	2025	2044
Plant 8	2025	2041	2040	2068
Plant 9	2025	2025	No retrofit	2030
Plant 10	2025	2030	No retrofit	2040
Plant 11	2025	2036	No retrofit	2046

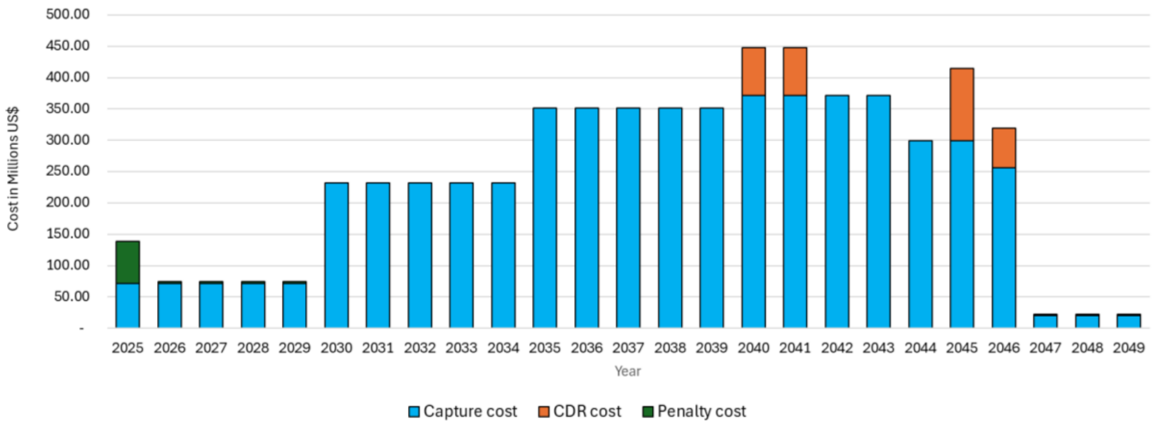

Figure 2. Cost distribution for optimal solution of case study 2

6. Conclusions

A MILP model was developed for optimal planning of the progressive fleet decarbonization towards net zero targets. The model uses a discrete-time formulation to time carbon capture retrofits to meet periodic emissions reduction check points; it also allows the purchase of CDR credits from an external supplier to deal with residual emissions. The model was first applied to a tutorial example, and then demonstrated on an industrial case study based on cement plants in Poland. Results show that carbon neutrality can be achieved optimally by retrofitting 5 out of 11 plants, and then using CDR credits to offset the remaining emissions. The model itself is generic and can be applied to any fleet of GHG emissions point sources, whether stationary (e.g., power plants, steel mills) or mobile (e.g., aircraft, ships). Future work can extend this model by introducing multiple internal decarbonization and CDR options. It can also be scaled up for planning the decarbonization of entire geographic regions. More sophisticated variants can be developed to model government-industry interactions, parametric uncertainties, and endogenous technology learning curves.

Nomenclature

i – index for plant
k – index for period

Decision variables
b_i – binary variable that indicates a retrofit in *i*
$\mathrm{CaptureCost}_k$– costs incurred for CO_2 capture
$\mathrm{CDRCost}_k$– cost incurred due to CDR
e_k – emissions in period *k*
$\mathrm{PenaltyCost}_k$– costs due to penalty
t_i^{start} – time when retrofit is activated initially

x_{ik}– binary variable that indicates activation of retrofit in plant *i* in period *k*
y_{ik} – carbon credits in plant *i* in period *k*

Parameters
BE_i – baseline emissions of plant *i*
C_i– unit cost for CO_2 capture,
CDR_k – unit cost for carbon credits in period *k*
$\mathrm{CDR}_k^{\mathrm{CAP}}$ – CDR cap in period *k*
$\mathrm{E}_k^{\mathrm{CAP}}$ – emissions cap in period *k*

RR_i– removal rate in plant *i*
$\mathrm{TL}_i, \mathrm{TU}_i$ – earliest and latest times of retrofit activation
Z_{ik} – binary parameter that indicates if plant *i* is operational in period *k*

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