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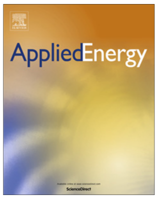

A multi-period optimisation model for planning carbon sequestration retrofits in the electricity sector

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HIGHLIGHTS

- A generic mathematical model is developed for multi-period CCS retrofit planning.
- The model minimises the cost of retrofitting power plants to meet the emission limit.
- The model is applied to case studies of Malaysia and Taiwan.
- The linearity of the model guarantees global optimality for the solutions obtained.

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ABSTRACT

Carbon capture and storage (CCS) is a low-carbon technology aiming to prevent carbon dioxide (CO_2) generated in large industrial facilities (e.g. power plants) from entering the atmosphere, thus mitigating human-caused climate change. CCS is deemed to be one of the most promising approaches to reduce industrial CO_2 emissions on a global scale, in addition to energy efficiency enhancement and increased use of renewables. This paper presents a mathematical programming model for multi-period planning of power plant retrofits with carbon capture (CC) technologies. The model allows for energy penalties due to CC retrofits and the need for compensatory power generation, as well as variations in technological parameters (such as electricity costs) over time. Furthermore, the model is formulated as a mixed integer linear programme (MILP), for which global optimality is guaranteed if a solution exists. Two case studies on carbon-constrained energy sector planning are presented to illustrate the proposed approach. Further analysis is carried out to examine the effect of the cost limit on the total increase in power generation cost.

1. Introduction

The exploitation of fossil fuels such as coal and oil has caused serious environmental pollution and the build-up of atmospheric carbon dioxide (CO_2) since the Industrial Revolution, with the latter fact being the most important long-lived “forcing” of climate change [1]. With global concern about resource depletion, environmental emissions and climate change, which are among the key drivers of sustainability, it has become pressing for countries around the world to commit to reducing greenhouse gas (GHG) emissions and mitigating global warming, particularly after COP21. Carbon capture and storage (CCS) is considered critical in a portfolio of low-carbon technologies for combating climate change [2], in addition to renewables and end-use energy efficiency. According to Energy Technology Perspectives 2016 [3], CCS would contribute 12% of the cumulative emissions reductions in the 2 °C Scenario (2DS) over the period 2013–2050, against a business-as-usual scenario. Furthermore, CCS is shown to be an integral part of any lowest-cost mitigation scenario with the increase in long-term global average temperature significantly less than 4 °C (e.g. 2DS) [4].

CCS involves capturing CO_2 from the use of fossil fuels in electricity generation and industrial processes. Carbon capture (CC) technologies include pre-combustion capture (in integrated gasification combined cycle (IGCC) plants) [5,6], post-combustion capture (using flue gas scrubbing) [7,8], oxy-fuel combustion [9] and chemical looping combustion (CLC) [10,11]. For any of these techniques, the captured and compressed CO_2 is then transported (commonly by pipeline) and injected into a sink (typically a geological reservoir) for permanent storage. Possible sinks include deep saline aquifers, inaccessible coal seams and depleted oil/gas reservoirs [12,13]. CC may also be carried out in conjunction with

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Nomenclature

Indices and sets$i \in \mathbf{I}$

	power sources
$i \in \mathbf{I}^{F}$	fossil-based power sources
$i \in \mathbf{I}^{NF}$	non-fossil power sources
$k \in \mathbf{K}$	CC technologies
$t \in \mathbf{T}$	time periods

Parameters

C^{CP}	carbon emission factor of compensatory power generation ($kgCO_2/kW\,h$)
C_i	carbon emission factor of power source i ($kgCO_2/kW\,h$)
D	discount rate (%)
E_t^{lim}	emission limit in time period t (Mt/y)
L_{ikt}	power loss factor associated with CC technology k for power source i in time period t
P_{it}	power output from source i in time period t (TW h/y)
RR_{ikt}	carbon removal ratio of CC technology k for power source i in time period t
α_i^{max}	maximum extent of CC retrofitting for power source i
α_i^{min}	minimum extent of CC retrofitting for power source i
β_{ikt}	relative cost of electricity from the retrofitted capacity of power source i using CC technology k in time period t
β_t^{RE}	relative cost of electricity from renewables in time period t
Δ_t	length of time period t (y)
ε	limit for the increase in overall electricity cost from the baseline (%)
Γ	large positive number

Variables

e_{it}^{R}	emissions from the retrofitted capacity of power source i in time period t (Mt/y)
e_{it}^{U}	emissions from the unmodified capacity of power source i in time period t (Mt/y)
p_{it}^{loss}	power loss from source i in time period t (TW h/y)
y_{it}	binary indicating if power source i is retrofitted in time period t
z_{ik}	binary indicating the decision to use CC technology k for power source i
α_{it}	fraction of the retrofitted capacity of power source i in time period t
γ_{it}	relative cost of electricity from the retrofitted capacity of power source i in time period t

enhanced oil recovery (EOR) [14] or enhanced coal bed methane (ECBM) recovery [15], to enable both CO_2 utilisation and storage. CCS is thus able to mitigate climate impacts by preventing large amounts of CO_2 from being released into the atmosphere.

As a transitional technology to a sustainable low-carbon economy, CCS allows the continued use of fossil fuels under carbon emission constraints. This aspect is critical given the world's continued dependence on fossil energy [16], which is still relatively reliable and cheap compared with most forms of renewable energy. Moreover, fossil energy appears to be more socially acceptable than nuclear energy [17] – the only other major low-carbon option currently available. Fossil fuel power plants account for a significant share of the world's CO_2 emissions, and are thus a prime candidate for CCS. Retrofitting power plants for CC, however, entails major capital costs as well as reductions in both thermal efficiency and power output [18,19]. These penalties ultimately result in an increase in the cost of electricity generation, relative to comparable unmodified power plants. Therefore, the deployment of CCS requires systematic sectoral planning so as to avoid power shortages (due to energy losses from CC) and minimise the increase in power generation cost.

For energy sector planning with CO_2 emission constraints (for climate change considerations), carbon-constrained energy planning (CCEP) has emerged as a relatively new area of research to address emission reduction issues in a systematic manner [20]. Several techniques were developed under the framework of carbon emission pinch analysis (CEPA). Tan and Foo [20] first presented a graphical procedure using energy planning composite curves to determine the optimal energy allocation to meet the energy demands and emission limits, whilst minimising the use of zero-carbon energy sources. The concept of CEPA was later extended for cases with land availability [21] and water footprint constraints [22], using algebraic and graphical tools respectively, as well as segregated targeting for multiple sectors/zones using pinch-based optimisation [23] and insight-based approaches [24]. For energy planning problems with multi-footprint constraints, a superstructure-based mathematical model was developed by Pękala et al. [25]. In addition, there have been several applications of CEPA in energy planning for Ireland [26,27], New Zealand [28–30], California [31] and China [32].

CCEP was then extended for planning CCS deployment in the power generation sector, focusing on the implications of retrofitting power plants for CC. Various pinch-based [33–35] and mathematical programming techniques [25,36,37] have been used to account for the interplay between CO_2 emission reductions and power losses. The latter necessitate compensatory power to be generated from new power plants or imported from adjoining regions. Planning of power generation systems taking into account multiple low-carbon options (including CCS) has also been demonstrated [38–40]. These methods can, on a static (single-period) basis, determine the minimum extent of CC retrofitting in a fleet of power plants (hence minimised power losses and compensatory power generation) to meet the emission limit.

To take account of energy demand growth and variations in key parameters (e.g. emission limits, electricity costs, etc.) over time, multi-period planning has been proposed. Chen et al. [41] developed a deterministic linear programming (LP) model named PPOM-CHINA with consideration of negative externalities apart from carbon emissions. Their model was applied to a case study of China's power planning over the period 2015–2030. Betancourt-Torcat and Almansoori [42] developed a multi-period stochastic programming model for the optimal design of electric power systems. Their model considers different supply options for natural gas and electricity imports as well as uncertainty in the gas price, but is restricted to planning the United Arab Emirates' power infrastructure.

Instead of determining the optimal installed capacity and power generation mixes over the planning horizon, Ooi et al. [43] extended the previous single-period techniques [33,34] to address the multi-period problem of planning CC retrofits in the power generation sector based on projected energy mix data. However, their automated targeting approach does not seem very straightforward in handling CCEP problems, and is subject to the inconvenience of having to calculate the carbon intensity levels beforehand. On the other hand, both the energy and CO_2 cascades [34,43] assume a "carbon" driving force, which does not