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Fuzzy optimization of multi-period carbon capture and storage systems with parametric uncertainties

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ABSTRACT

Carbon capture and storage (CCS) is an important technology option for reducing industrial greenhouse gas emissions. In practice, CO_2 sources are easy to characterize, while the estimation of relevant properties of storage sites, such as capacity and injection rate limit (i.e., injectivity), is subject to considerable uncertainty. Such uncertainties need to be accounted for in planning CCS deployment on a large scale for effective use of available storage sites. In particular, the uncertainty introduces technical risks that may result from overestimating the limits of given storage sites. In this work, a fuzzy mixed integer linear program (FMILP) is developed for multi-period CCS systems, accounting for the technical risk arising from uncertainties in estimates of sink parameters, while still attaining satisfactory CO_2 emissions reduction. In the model, sources are assumed to have precisely known CO_2 flow rates and operating lives, while geological sinks are characterized with imprecise fuzzy capacity and injectivity data. Three case studies are then presented to illustrate the model. Results of these examples illustrate the tradeoff inherent in planning CCS systems under parametric uncertainty.

Keywords: Carbon capture and storage; Technical risk; Fuzzy mixed integer linear programming; Data uncertainty; Source-sink matching; Optimization

1. Introduction

Carbon footprint (CF) is one of the most important indicators in assessing sustainability of a product or service (Čuček et al., 2012). It is a measurement of CO_2 emissions associated with a given product or service on a life cycle basis (Wiedmann and Minx, 2008). As of 2010, worldwide CO_2 emissions were in excess of 30 Gt/y, and are expected to continue to increase in the coming decades. A major portion of CO_2 emissions comes from the power generation sector, particularly power plants running in fossil fuels (IEA, 2012). The reduction of CO_2 emissions particularly in electricity generation is thus one of the most important means to mitigate climate change. Low-carbon strategies such as efficiency enhancement, use of renewable sources, and fuel substitution can reduce these greenhouse gas emissions, but may also be subject to their respective limitations. For the next few decades, fossil fuels will remain the major source of energy, especially for electricity generation (Bhattacharyya, 2009). In order to meet the growing global demand for energy, technologies are needed that would enable the use of fossil fuels while reducing CO_2 emissions. One of these technologies is carbon capture and storage (CCS) (Davison et al., 2001; Pires et al., 2011).

CCS technology involves first capturing CO_2 from combustion products through various physical or chemical processes, and then injecting the captured CO_2 into reservoirs for permanent storage (Gibbins and Chalmers, 2008; Davison et al., 2001). Capture techniques includes post-combustion CO_2 removal via flue gas scrubbing using a solvent (Wang et al., 2011); precombustion capture, which converts fuel into H_2-rich gas and a separate CO_2-rich stream for sequestration (Kanniche et al., 2010); and oxyfuel and chemical looping combustion, both of which burn fossil fuels in the absence of atmospheric nitrogen to yield exhaust gas consisting mainly of CO_2 and water vapor (Wall et al., 2009; Adanez et al., 2012). In all cases, the captured CO_2 is then transported and stored in geological sinks, such as unmineable coal deposits, saline aquifers and depleted oil or gas reservoirs (Gibbins and Chalmers, 2008;

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Nomenclature

Sets

i	index for sources ($i = 1, 2, 3, \ldots m$)
j	index for sinks ($j = 1, 2, 3, \ldots n$)

Variables

λ	overall degree of satisfaction
λ_G	degree of satisfaction for the fuzzy goal
λ_j^B	degree of satisfaction for the fuzzy storage capacity
λ_j^C	degree of satisfaction for the fuzzy injection rate limit
y_{ij}	number of power plant units retrofitted to capture CO_2 in source i to sink j
x_{ij}	binary variable that determines whether a connection exists between source i and sink j
B_j	utilized storage limit of sink j (Mt)
C_j	utilized injection rate limit of sink j (Mt/y)

Parameters

A_i	CO_2 flow rate of source i per power plant unit (Mt/y)
N_i	number of power plant units
T_i^{start}	time at which source i starts to operate (y)
T_i^{end}	time at which source i ceases to operate (y)
T_j	time at which sink j becomes available (y)
B_j^{min}	lower limit of the storage capacity of sink j (Mt)
B_j^{max}	upper limit of the storage capacity of sink j (Mt)
C_j^{min}	lower limit of the injection rate limit of sink j (Mt/y)
C_j^{max}	upper limit of the injection rate limit of sink j (Mt/y)

Ball and Wietschel, 2009). The latter two options potentially allow additional revenue through the production of additional fuel output from reservoirs with declining productivity. CCS is regarded as an important technology for contributing to the much-needed massive reductions in worldwide CO_2 emissions in the coming decades (Butt et al., 2012). For example, without CCS, it is estimated that the cost for achieving 50% reduction by 2050 will increase by 70% (IEA, 2010).

Numerous methods have been developed for decision support in the planning of large-scale CCS systems. These techniques include grid-wide models, pipeline infrastructure models and source-sink models. One of the earliest models is by Turk et al. (1987) which involve profit maximizing approach for pipeline infrastructures in CO_2 sequestration with enhanced oil recovery (EOR). Benson and Ogden (2003) developed a model for minimum cost pipeline network which considers the effect of uncertainties in the network through time. Ordorica-Garcia et al. (2009), Elkamel et al. (2009) and Nakata et al. (2011) designed grid-wide energy models for energy systems with low carbon technologies such as CCS and integrated gasification combined cycle (IGCC) system. A grid-wide model that involves carbon constrained planning using CCS technologies has been developed using both linear optimization (Pekala et al., 2010) and pinch analysis techniques (Tan et al., 2009, 2010). These techniques considered retrofitting existing power plants with CCS technologies and compensating for power losses due to retrofitting. Genetic algorithm (GA) approach for CCS systems for pipeline infrastructures with multiple injection sites has been developed (Fimbres-Weihs et al., 2011). Infrastructure models have been developed for building a CCS system in a certain geographic region in which cost of pipeline infrastructures is at minimum. These models include SimCCS and SimCCS^{TIME} which incorporates structural parameters such as pipeline sizes in a static (Middleton and Bielicki, 2009) and dynamic (Middleton et al., 2012a,b) framework, respectively. Source-sink models for CCS planning have been developed using both discrete-time (Tan et al., 2012a) and continuous-time (Tan et al., 2012b; Lee and Chen, 2012) approaches. Most such models assume the existence of precise parameters; however, it is now well understood that neglecting uncertainties (e.g., in the properties of geological reservoirs) would incur significant technical risks in the design of CCS networks (Middleton et al., 2012a,b). Diamante et al. (2013) developed a pinch-based sensitivity analysis technique to determine the effect of uncertainties of sink parameters and source operating lives; they found that a significant change in the amount of capturable CO_2 may result from parametric uncertainties. Other factors that have been considered in CCS planning include carbon prices to incentivize CO_2 emissions management given variable power generation (Middleton and Eccles, 2013). Recent literature also includes pinch based targeting techniques for source-sink matching only with precise sink parameters, subject to capacity, injectivity and availability constraints (Tan et al., 2012a,b; Ooi et al., 2012, 2013; Diamante et al., 2014) and energy networks with CCS coupled with EOR (Middleton, 2013). Lee et al. (2014) proposed a unified MILP model to account for both grid loss and source-sink matching aspects of CCS deployment. Recent application of infrastructure models for CCS includes decision support system for CCS deployment in the Beijing–Tianjin–Hebei region in China (Sun and Chen, 2013).

The key research gap addressed in this paper is the development of an approach for the effective matching between CO_2 sources and geological sinks, where technical risks resulting from uncertainties in the sink parameters (i.e. storage capacity, injection rate) are considered. Sink parameters relevant to CCS applications are storage capacity and injection rate limits (i.e., injectivity). These properties in turn are based on geological features such as porosity (i.e. void space in geological formations) and permeability (i.e. pore connectivity), respectively (Holloway, 2007). The characteristics of reservoirs are measured through geological site surveys and there is often lack of complete information about a given geological site. Such gaps in data result in significant technical risk in planning CO_2 storage (Bachu et al., 2007). In source-sink matching, highly reliable estimates of these parameters are required for effective source-sink matching (Bradshaw et al., 2007). However, in general, more precise estimates may only be possible at added cost (if at all) through additional geological surveys of storage sites. Uncertainties can also arise from sampling errors due to the non-uniformity of properties across a candidate storage site (Middleton et al., 2012a,b). Different assessments of sink capacities presented for reservoirs such as in Germany and Northern Europe (Holler and Viebahn, 2011), Australia (Bachu and Adams, 2003), China (Pearce et al., 2011) and Estonia (Shogenova et al., 2011) shows large uncertainties in capacity estimates. For instance, different capacity calculations yielded a wide range of figures for the Viking Alberta reservoir in Canada, ranging from 92 to 200 Gt (Bachu and Adams, 2003). A recent study on modeling these uncertainties was conducted by Ashraf et al. (2013), who used