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Optimal Planning for Regional Carbon Capture and Storage Systems under Uncertainty

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Increasing emissions of greenhouse gases (GHGs) have been identified as the main contributor to global warming and climate change. Carbon dioxide (CO_2) is the primary anthropogenic GHG. Carbon capture and storage (CCS) is widely recognized as a key mitigation technology that can significantly reduce CO_2 emissions during combustion. It involves capturing CO_2 from large stationary sources and subsequently storing it in various reservoirs such as depleted oil or gas reservoirs, saline aquifers and deep unmineable coal seams. In this work, a finite-scenario based two-stage stochastic mixed integer linear programming (MILP) model is developed for planning the retrofit of power plants with carbon capture (CC) technology and the subsequent CO_2 source-sink matching in CCS supply chains under uncertainty. This model can be used to select appropriate sources, capture technologies and sinks and maximize the amount of captured and stored CO_2 under the presence of uncertainty. Furthermore, to control risk at the optimal deployment of CCS systems, probabilistic financial risk metric is incorporated into the model. A case study is used to demonstrate the application of the proposed model. The computational results show that after risk management, risk of the expectation amount of captured and stored CO_2 is reduced.

1. Introduction

Increasing greenhouse gas emissions (GHG) is considered as one of the main reasons for global warming. Carbon dioxide (CO_2) is the most dominant human-influenced greenhouse gas, whose total emissions have increased from about 22.7 billion t to about 35.3 billion t/y (56 % higher) between 1990 till 2013 (Van der Hoeven, 2014). Carbon capture and storage (CCS) is one of the technologies that contribute to the decrease in GHG emissions. It involves a two-step procedure: first, capture CO_2 via physical or chemical process from the flue gas; then, compress and transport the captured CO_2 into various sinks including saline aquifers, inaccessible coal deposits and depleted oil or gas reservoirs, provided that these sinks are suitable for storage based on geological surveys of geochemical, seismic risk or other physical consideration (Holloway, 2007). Thus, CCS is able to mitigate climate impacts by preventing CO_2 from releasing into atmosphere. In practice, CCS systems will face uncertainties which may come from social, economic, environmental, and political factors.
Recently, extensive researches have been developed to aid in planning the commercial deployment of CCS. Pinch-based (Tan et al., 2009) approaches became useful and provided significant insights into CO_2 allocation network. Pinch analysis approaches also addressed multi-regional CCS systems with geographic clustering (Diamante et al., 2014). Mathematical programming approaches were used to determine the best source-sink matching for CCS networks in detail using continuous-time (Tan et al., 2012) and discrete-time (Tan et al., 2013) approaches. A unified MILP model was proposed to address selection of CO_2 sources and source-sink matching (Lee et al., 2014). As for the infrastructure aspect, a SimCCS model was developed to match sources and sinks (Middleton et al., 2009). A hierarchical and multi-scale framework was developed to design a CO_2 capture and storage and a capture and utilization supply chain networks (Hasan et al., 2015). Risk management for CO_2 networks were developed by addressing the uncertainties in the available data using fuzzy optimization (Tapia and Tan, 2014) and robust programming (He et al., 2012). Design under uncertainty of CCS infrastructure

considering cost, environmental impact, and preference on risk was also studied (Lee et al., 2017). Analytic hierarchy process data envelopment analysis was developed to select oil and gas reservoirs (Tapia et al., 2017). In previous work, the CC retrofit planning and source-sink matching were commonly studied separately even there is strong interaction between the two systems. And it has been demonstrated that uncertainties confronted in CCS systems may affect both the CO_2 emissions reduction target and network topology. This study proposes a two-stage stochastic mixed-integer linear programming (MILP) model to achieve the optimal retrofit planning of power plants with CC technology and CO_2 source-sink matching in CCS supply chains with considering uncertainties in sink physical constraints and investment limit. To control risk at the optimal deployment of CCS systems, probabilistic financial risk metric is incorporated into the model, which is used to represent the decision maker's tolerance of risk.

2. Problem Statement

The formal problem statement addressed in this paper is as follows. The objective is to maximize the amount of captured and stored CO_2 by planning retrofit of power plants and matching CO_2 sources with sinks and minimize the risk level at the optimal deployment of CCS systems.

- The CCS system is assumed to be comprised of i CO_2 sources, j CO_2 sinks and the planning horizon consists of t time intervals. Each time interval is represented by Δt. The planning horizon spans the operating lives of all CO_2 sources and sinks in the system.
- Each CO_2 source has a captured CO_2 flow rate depending on the CC technology used. The start and end of the operating life of each source (Y_{it}) is predefined.
- Each CO_2 sink is characterized by an upper limit for both CO_2 injection rate and storage capacity, as determined by its physical characteristics. The earliest time of availability of each sink (Y_{jt}) is also specified.
- It is assumed that any given CO_2 source i may be connected to only one CO_2 sink j (i.e., no branching is allowed); however, a CO_2 sink j may be linked to multiple CO_2 sources.
- The fixed CO_2 removal and energy loss ratio as well as a fixed relative or dimensionless cost of each capture technology k are given.
- The uncertainties arise from the sink characters and the investment limit Γ. The corresponding probability distribution of each scenario p_s is given.

3. Model formulation

For the case of uncertainties described by probability distributions, a stochastic two-stage MILP model is formulated. This model requires that data be specified for CO_2 sources and sinks, CC technologies, compensatory power generation and probability distributions for each scenario. With these input data, the model is able to determine an optimal CO_2 allocation network maximizing the amount of CO_2 captured and stored within the given system.

$$\text{Max } E\left[storage\right] = \sum_{s\in S} p_s (ACS_s - ACE_s) \tag{1}$$

$$\text{Min } Risk(\Omega) = \sum_{s\in S} p_s \times z_s \tag{2}$$

$$\text{Max } \sum_{s\in S} p_s (ACS_s - ACE_s) - \rho \sum_{s\in S} p_s \times z_s \tag{3}$$

The idea behind Eq(1) is that the decision maker wants to maximize the expected amount of captured and stored CO_2. Eq(2) is to minimize the financial risk at a given target Ω. Eq.(3) includes a goal programming weight ρ in the objective function to obtain a trade-off between expectation and risk controlled by the decision maker. Y_{it} and Y_{jt} denote the operation time for source i and sink j respectively.

$$ACS_s = \sum_{i\in I}\sum_{j\in J}\sum_{t\in T} F_{ijts}\Delta t \quad \forall s \in S \tag{4}$$

$$ACE_s = f\sum_{i\in I}\sum_{j\in J} E_{its}^{loss}\Delta t \quad \forall s \in S \tag{5}$$

$$T_i^{\min} z_{ij} \le \sum_{t\in T} y_{ijts}\Delta t \le H z_{ij} \quad \forall i \in I, \forall j \in J, \forall s \in S \tag{6}$$

$$y_{ij,t-1,s} - y_{ijts} \le 1 - Y_{it} \quad \forall i \in I, \forall j \in J, \forall t \in T, \forall s \in S \tag{7}$$

$$y_{ijts} \le Y_{it} \quad \forall i \in I, \forall j \in J, \forall t \in T, \forall s \in S \tag{8}$$

$$F_{ijts} \le F_i y_{ijts} \quad \forall i \in I, \forall j \in J, \forall t \in T, \forall s \in S \tag{9}$$

$$F_i(y_{ijts} - 1) \le F_{ijts} - EM_i \sum_{k \in K} RR_{ik} x_{ik} \le 0 \quad \forall i \in I, \forall j \in J, \forall t \in T, \forall s \in S \tag{10}$$

For Eq(4)-(5), ACS_s is the amount of captured and sored CO_2 and ACE_s is the additional emissions from compensatory power plants needed to compensate for CC energy losses. Eq.(6)-(10) are used to calculate the captured CO_2 flow rate F_{ijts}. y_{ijts} is a binary variable that denotes the operation time in scenario s.

$$\sum_{i \in I} F_{ijts} \le F_j Y_{jt} \quad \forall j \in J, \forall t \in T, \forall s \in S \tag{11}$$

$$\sum_{i \in I} \sum_{t \in T} F_{ijts} \Delta t \le Q_j \quad \forall j \in J, \forall s \in S \tag{12}$$

$$\sum_{k \in K} x_{ik} \le 1 \quad \forall i \in I \tag{13}$$

$$\sum_{j \in J} z_{ij} = \sum_{k \in K} x_{ik} \quad \forall i \in I \tag{14}$$

$$\sum_{j \in J} z_{ij} \le 1 \quad \forall i \in I \tag{15}$$

$$x_{ik} \le T_{ik} \quad \forall i \in I, \forall k \in K \tag{16}$$

The physical constraints are given by Eq(11)-(12), where F_j and Q_j denote the limit of injection rate and capacity of sink j. For each CO_2 source to be captured, only one technology and only one sink can be chosen as given by Eq(13)-(15). Eq(16) defines the forbidden (T_{ik}=0) and allowable (T_{ik}=1) matches between technologies and sources. z_{ij} is a first-stage binary variable that denotes the connection between source i and sink j. x_{ik} is a first-stage binary variable that denotes the selection of capture technology k of source i.

$$P_i(\sum_{j \in J} y_{ijts} - 1) \le p_{its}^{loss} - P_i \sum_{k \in K} L_{ik} x_{ik} \le 0 \quad \forall i \in I, \forall t \in T, \forall s \in S \tag{17}$$

$$p_{its}^{loss} \le P_i \sum_{j \in J} y_{ijts} \quad \forall i \in I, \forall t \in T, \forall s \in S \tag{18}$$

$$C_i^U(Y_{it} - \sum_{j \in J} y_{ijts} - 1) \le c_{its} - C^{up} P_i \le C_i^U(1 - Y_{it} + \sum_{j \in J} y_{ijts}) \quad \forall i \in I, \forall t \in T, \forall s \in S \tag{19}$$

$$C_i^U(\sum_{j \in J} y_{ijts} - 1) \le c_{its} - \sum_{k \in K} C_K^{RP} P_i (1 - L_{ik}) x_{ik} \le C_i^U(1 - \sum_{j \in J} y_{ijts}) \quad \forall i \in I, \forall t \in T, \forall s \in S \tag{20}$$

$$\sum_{i \in I} \sum_{t \in T} c_{its} \Delta t + C^{NP} \sum_{i \in I} \sum_{t \in T} p_{its}^{loss} \Delta t \le \Gamma C^{up} \sum_{i \in I} \sum_{t \in T} P_i Y_{it} \Delta t \quad \forall s \in S \tag{21}$$

Eq(17)-(18) are used to determine the power losses p_{its}. The power generation cost c_{its} can be calculated using Eq(19)-(20). Eq(21) limits the investment cost of the system, which means that after retrofitting, the cost cannot exceed a dimensionless value Γ.

4. Case Study

In this section, the proposed model is demonstrated through a hypothetical but realistic case study. The case study is adapted from Tan et al. (2009). It consists of 6 power plants as CO_2 sources, 3 geological reservoirs as

CO_2 sinks. The planning horizon of the carbon capture and storage systems is 50 years. The minimum viable duration of CCS for each plant is assumed to be 20 years. The source and sink data are shown in Table 1 and Table 2, respectively. Two CC retrofit technologies are considered in this case study, namely flue gas scrubbing (FGS) and oxy-fuel combustion (OFC). Plants 3 and 6 are unsuitable for the OFC option. The CO_2 removal ratios of FGS and OFC are assumed to be 0.8 and 0.9, respectively and the relative power losses are 0.2 and 0.25, respectively. Due to the energy losses of CC retrofit, compensatory power is required. The emission factor f is assumed as 0.001 Mt/(MW·y). The unit electricity produced by retrofitted plants is 60 % more expensive than that produced by the unmodified plants; likewise the unit generated by the compensatory plants is 40 % more expensive than unmodified plants. The objective is to maximize the amount of captured and stored CO_2 without increasing the overall electricity cost by more than 30 %, i.e. $\Gamma = 1.3$ (In BASE scenario the overall investment is no more than 1.3 times of the unmodified plants). Three uncertainty scenarios of injection rate, storage capacity and investment at LOW, BASE and HIGH are investigated. LOW and HIGH scenarios are 0.8 and 1.2 times of the BASE one. The probability of corresponding scenario is assumed to be 25 %, 50 % and 25 %. Based on these assumptions, we can generate a total of 3 × 3 × 3 = 27 scenarios. The scenarios are shown in Figure 1.

Table 1: Source data for case study

Plant/Source	Power P_i (MW)	Emissions EM_i (Mt)	Time of operation (y)
1	Coal	120	0-30
2	Coal	200	0-40
3	Coal	62.5	5-30
4	Coal	240	10-40
5	Natural gas	200	0-40
6	Natural gas	120	10-50

Table 2: Sink data for case study

Sink	Injection limit (Mt/y)	Start time (y)	Maximum storage (Mt)
MA	0	0	200
MB	10	10	400
MC	15	15	250

4.1 Stochastic model without risk management

To manage the risk for the above-described problem, the stochastic model was solved first, obtaining the solution that maximizes the expected amount of stored CO_2, without taking risk into account. The objective is the net expected stored CO_2 quantity, which is calculated by Eq(1). It means that the net expected stored CO_2 quantity is the difference between the captured and stored amount of CO_2 and the additional emissions from new power plants needed to compensate for CC energy losses. In this case study, there are 27 scenarios as shown in Figure 1. The optimal planning results for the systems are obtained by solving the stochastic programming with 27 scenarios. The maximum expectation amount of stored CO_2 is found at 551.57 Mt. The risk curve of this solution is shown in Figure 2a. Easily found that the risk at optimal solution 551.57 Mt is about 40 %. It means that under the uncertainties described above, solutions without considering risk may fail to store 551.57 Mt CO_2 with a probability of 40 %.

4.2 Stochastic model with risk management

As discussed above, a major limitation of the stochastic model is that it considers “expected outcomes” of the problem objective without explicitly taking into account its variability. To reduce risk level of the deployment of CCS systems, the risk objective described in Eq(2) is incorporated into the stochastic programming model and get the objective as given by Eq.(3). Goal programming weight ρ in Eq(3) is used to obtain solutions where the relative importance of expectation and risk are controlled by the decision maker, controlling the shape of the risk curve. Here 551.57 Mt (optimal solution of the stochastic model) is chosen as the target and the 27 scenarios are also used for the calculation. The comparison of stored CO_2 probability distribution for the results before and after risk management is given in Figure 2b.

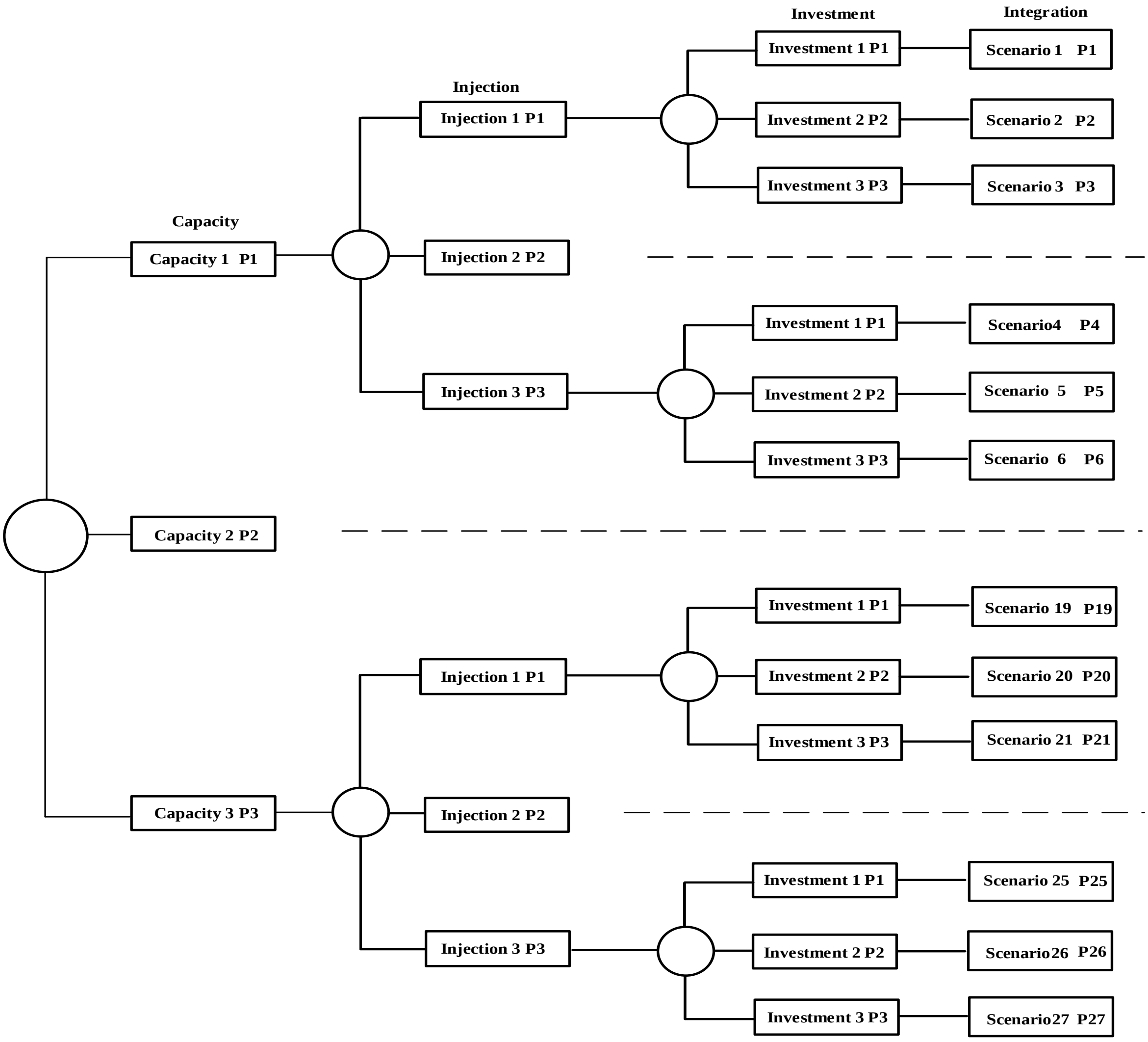

Figure 1: Scenario generation for the model

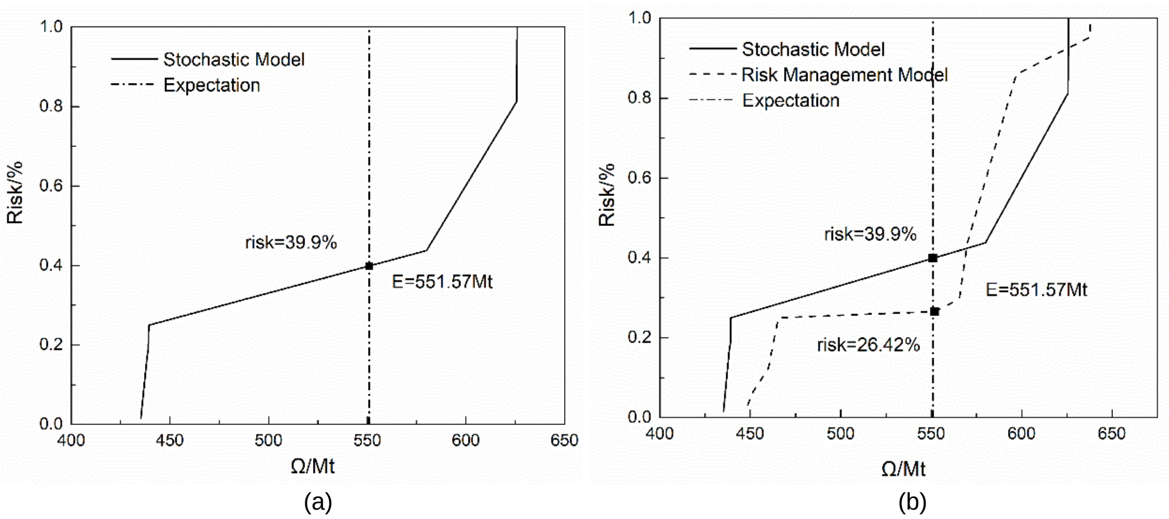

Figure 2: (a) Risk curve of the stochastic model. (b) Risk curve of the risk management model

As shown, the optimal solution of stochastic programming model features about 40 % probability that total amount of captured and stored CO_2 is lower than 551.7 Mt, whereas after risk management (the dash line), the risk at 551.57 Mt is only 26 %. It means that the risk of storing low amount of CO_2 has been significantly reduced after risk management, although the expected total stored CO_2 has decreased a little. Compared with the results of the stochastic model and risk management model, it can be found that the stochastic programming model with risk management is capable to reduce the risk level against uncertainty. It is found that uncertain parameters significantly affect not only the CCS allocation network configuration but also the operating conditions. The results show that the modeling of uncertainties is critical in the deployment of CCS systems.

5. Conclusions

This paper presents a methodology for the optimal design of carbon capture and storage system considering sink physical and investment limit uncertainty. It takes into consideration of the uncertainty that systems may confront. The effectiveness of the method is validated by a case study. The model is solved without considering risk and then incorporates risk management with stochastic programming models. Compared with the results of the stochastic model and risk management model, it can be found that the stochastic programming model with risk management is capable to reduce the risk level from 40 % to 26 % against uncertainty. Future work includes the extension of the current model to consider the uncertainty of carbon tax and to consider all the implications of uncertainty on the CCS allocation network.

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