CHEMICAL ENGINEERING TRANSACTIONS

VOL. 103, 2023

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

Guest Editors: Petar S. Varbanov, Panos Seferlis, Yee Van Fan, Athanasios Papadopoulos

ISBN 979-12-81206-02-1; **ISSN** 2283-9216

DOI: 10.3303/CET23103075

Optimal Planning of Carbon Capture and Storage (CCS) Systems with Neutrosophic Uncertainties

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Carbon capture and storage (CCS) is an important technology that mitigates the effect of climate change. It involves the capture of CO_2 from flue gas, transporting it through pipelines, and storing it underground in geological reservoirs. The characterization of the properties of geological reservoirs (i.e., storage capacity and flow rate limit) are subject to uncertainties. These uncertainties affect the planning of CCS systems, especially in determining which CO_2 sources are to be matched with geological sinks subject to capacity and injectivity constraints. In this study, a Neutrosophic Linear Programming (NeLP) model is developed for optimal planning of CCS systems considering these uncertainties modeled as neutrosophic sets. The model involves taking into account the degree of satisfaction when minimizing risks, the degree of dissatisfaction when overestimating storage parameters, and the degree of indeterminacy when defining accurate storage site parameters. A case study will be used to illustrate the model. The model was able to generate insights as to how much CO_2 must be injected into the geological reservoir to minimize the risks arising from uncertainty. The total CO_2 stored in geological reservoirs varies from one risk behavior to another.

1. Introduction

The effect of climate change globally has been an alarming issue that needs serious action from different countries. The drastic increase in CO_2 concentration in the atmosphere is attributed to the use of fossil fuels for energy production. Different technologies can contribute to the reduction of CO_2 emissions from industrial sources, and not a single technology can address the issue of climate change. These technologies include renewable energy as an alternative energy source, process efficiency improvements, and carbon capture and storage (CCS) technology. CCS is an important technology that allows the simultaneous use of fossil fuels for energy production and the reduction of CO_2 emissions from these sources. The technology involves the capture of CO_2 from flue gas, transporting it through pipelines, and storing it in geological reservoirs (Gibbins and Chalmers, 2008). The adaption of CCS technologies in a region consists of identifying multiple CO_2 sources for retrofitting CO_2 capture technologies and connecting these sources to multiple geological storage sites. Large-scale implementation of CCS requires systematic planning using mathematical approaches to generate the maximum benefit from the technology. However, uncertainties in the characteristics of the geological reservoir pose a significant challenge in the effective planning of CCS systems (Middleton et al., 2012). A mathematical model which captures the complex nature of the uncertainties in the characteristics of geological reservoirs is needed to optimize the system while managing the risks associated with these uncertainties.
Several mathematical approaches are proposed for the planning of CCS systems. A review of these approaches was made by Tapia et al. (2018), highlighting the important questions for developing future models for the planning and design of CCS systems. Tan et al. (2010) developed a model where the decision to retrofit power plants with CO_2 capture is considered. Multi-period optimization of CCS systems can be done in a discrete-time (Tan et al., 2013) or continuous-time (Tan et al., 2012) setting with an alternate formulation proposed (Lee and Chen, 2012). In these approaches, sources and sinks in the systems are matched, and the operation involved in a source-sink connection is scheduled. A fuzzy linear programming approach was developed by Tapia et al. (2014) for managing risk arising from fuzzy set-like uncertainties. Stochastic optimization approaches have been applied to the planning and design of carbon, capture, utilization, and storage (CCUS) systems under price

Paper Received: 15 February 2023; Revised: 30 May 2023; Accepted: 22 July 2023
Please cite this article as: Tapia J.F.D., 2023, Optimal Planning of Carbon Capture and Storage (CCS) Systems with Neutrosophic Uncertainties, Chemical Engineering Transactions, 103, 445-450 DOI:10.3303/CET23103075

uncertainties (Leonzio et al., 2020) and the planning of CCS systems under operational uncertainties (He et al., 2014). Region-wide optimization of CCUS systems is done by Wang et al. (2022), considering carbon life cycle metabolism analysis. These models have contributed to generating important insights into planning CCS systems in different settings. However, most of these models assume deterministic characteristics of storage sites except for the study by Tapia et al. (2014) and He et al. (2014). In this study, a neutrosophic set-based mathematical programming approach is applied to develop a model that incorporates the complex nature of the uncertainty of storage characteristics as neutrosophic sets.

Neutrosophic sets are mathematical objects that represent uncertainty as an extension of fuzzy sets (Zadeh, 1965) and intuitionistic fuzzy sets (Atanassov, 1986). It involves three components of membership, non-membership, and indeterminacy to describe the belongingness of an element to a set (Smarandache, 2006). It has been applied to different decision analysis tools such as data envelopment analysis (Abdelfattah, 2019), analytic hierarchy process (Abdel-Basset et al., 2017), and DEMATEL (Abdel-Basset et al., 2018). Several applications of tools that apply neutrosophic sets are in renewable energy selection (Azzam et al., 2022), evaluation of negative emissions technologies (Tapia, 2021), and site selection for waste-to-energy plant (Meng et al., 2023). These tools have been able to generate insights for policymakers to plan sustainable systems effectively. To date, neutrosophic sets in CCS have not yet been applied. In this study, neutrosophic sets will be applied to model the uncertainty in storage characteristics and manage the risks associated with it. A neutrosophic linear programming model (NeLP) is developed for this purpose. Each component of the neutrosophic set is represented in the NeLP model to characterize the uncertainty in storage characteristics.

The rest of the paper is organized as follows. Section 2 discusses the formal problem statement for the NeLP model, while Section 3 provides the details of the model, including the objective function, constraints, decision variables, and parameters. Section 4 discusses the case study to illustrate the model. Lastly, Section 5 discusses the conclusions and future works.

2. Problem statement

The formal problem statement for the CCS system is as follows:

- The system consists of *m* CO_2 sources and *n* geological sinks.
- Each CO_2 source *i* (*i* =1, 2, …m) is characterized as a point source capable of being retrofitted with a CO_2 capture technology that operates at a range of CO_2 flow rate from F^L_i to F^U_i Mt/y. The operating life of the source is fixed at ΔT_i y.
- Each sink is characterized by storage capacity and injectivity expressed as neutrosophic triplets [C^L_j, C^M_j, C^U_j] and [D^L_j, D^M_j, D^U_j]. This sink has a lower bound capacity and injectivity of C^L_j Mt and D^L_j Mt/y and an upper bound of C^U_j Mt and D^U_j Mt/y. It is assumed that the middle values C^M_j Mt and D^M_j Mt/y are the most possible estimates of capacity and injectivity. The lower bound represents a conservative estimate while the upper bound represents an optimistic estimate.
- The risks associated with estimating the characteristics of the geological can be described as a neutrosophic set which consists of three components – membership, non-membership, and indeterminacy. The membership component is represented as the degree of satisfaction towards minimizing risk for overestimating the storage parameters. Consequently, the non-membership is represented as the degree of dissatisfaction associated with increased risk. The indeterminacy captures the degree of inaccuracy of different levels of storage characteristics, being the most possible estimate is treated with the lowest indeterminacy.
- It is assumed that at the beginning of the planning horizon, all sources and sinks are available at the same time.
- The objective of maximizing the total CO_2 captured and stored is a fuzzy goal where the degree of satisfaction increases as the CO_2 stored increases. It is assumed that the perception of the decision maker for this goal is just fuzzy in nature.
- The model's objective is to maximize the aggregated neutrosophic components based on the overall degree of satisfaction, degree of dissatisfaction, and degree of indeterminacy. Figure 1a shows the neutrosophic nature of the storage characteristics, which are both applicable to capacity, while Figure 1b shows the fuzzy goal.
- Two parameters are established for adjusting the model depending on the risk appetite of the decision maker. The first one is the tolerance of the decision maker towards dissatisfaction (*TE*), while the second one is the tolerance of the decision maker towards indeterminacy (*TI*) of the storage characteristics estimate. These are also shown in Figure 1a.

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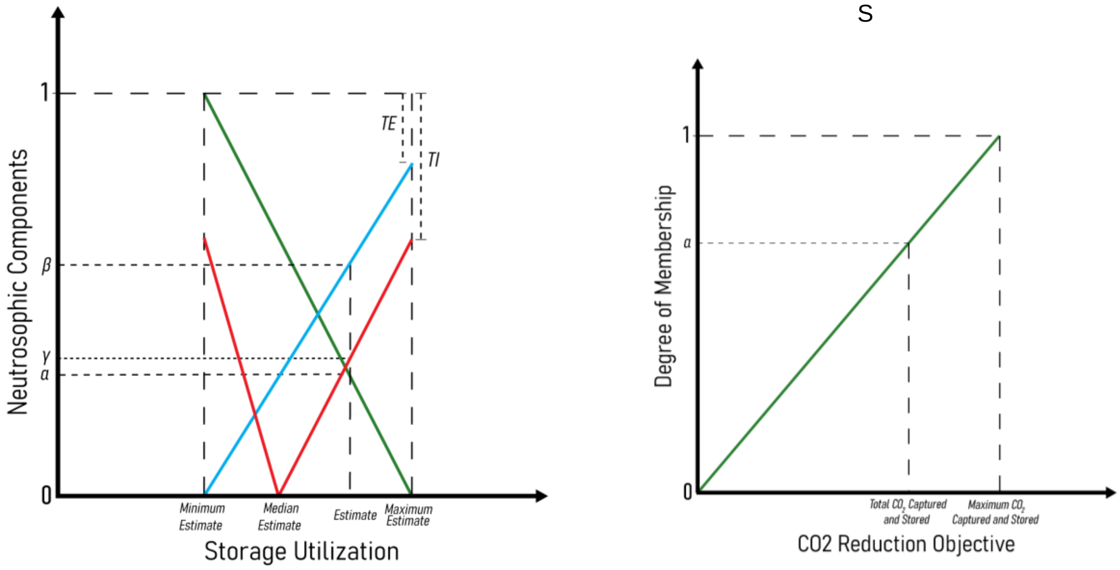

(a) (b)

Figure 1: Representation of the membership, non-membership, and indeterminacy of (a) neutrosophic storage characteristics and (b) fuzzy goal

3. Neutrosophic Linear Programming Formulation

The objective function of the NeLP model is to maximize the overall degree of satisfaction, α, and minimize the overall degree of dissatisfaction, β, and indeterminacy, γ. This objective is aggregated as a linear function in Eq(1)

$$\max \alpha - \beta - \gamma \tag{1}$$

Subject to:

$$\frac{\sum_i \sum_j \Delta T_i f_{ij}}{\sum_i \Delta T_i F_i^U} \geq \alpha \tag{2}$$

$$\frac{C_j - C_j^L}{C_j^U - C_j^L} \geq \alpha \qquad \forall j \tag{3}$$

$$\frac{D_j - D_j^L}{D_j^U - D_j^L} \geq \alpha \qquad \forall j \tag{4}$$

$$\frac{C_j^U - C_j}{C_j^U - C_j^L} \leq \frac{\beta}{1 - TE} \qquad \forall j \tag{5}$$

$$\frac{D_j^U - D_j}{D_j^U - D_j^L} \leq \frac{\beta}{1 - TE} \qquad \forall j \tag{6}$$

$$\frac{C_j - C_j^M}{C_j^U - C_j^M} \leq \frac{\gamma}{1 - TI}; \frac{C_j^M - C_j}{C_j^M - C_j^L} \leq \frac{\gamma}{1 - TI} \qquad \forall j \tag{7}$$

$$\frac{D_j - D_j^M}{D_j^U - D_j^M} \leq \frac{\gamma}{1 - TI}; \frac{D_j^M - D_j}{D_j^M - D_j^L} \leq \frac{\gamma}{1 - TI} \qquad \forall j \tag{8}$$

$$\sum_i \Delta T_i f_{ij} \leq C_j \qquad \forall j \tag{9}$$

$$\sum_i f_{ij} \leq D_j \qquad \forall j \tag{10}$$

$$C_j^L \le C_j \le C_j^U \qquad \forall j \qquad (11)$$

$$D_j^L \le D_j \le D_j^U \qquad \forall j \qquad (12)$$

$$F_i^L b_{ij} \le f_{ij} \le F_i^U b_{ij} \qquad \forall i,j \qquad (13)$$

$$\sum_j b_{ij} \le 1 \qquad \forall i \qquad (14)$$

$$b_{ij} \in \{0,1\} \qquad \forall i,j \qquad (15)$$

$$f_{ij} \ge 0 \qquad \forall i,j \qquad (16)$$

The decision variables for this model are the flow rate of CO_2 that will be allocated from source *i* to sink *j* denoted by f_{ij} and the binary variable, b_{ij} that denotes whether the connection from source *i* to sink *j* is to be made (b_{ij} = 1) or not (b_{ij} =0). The overall degree of satisfaction, α, is the minimum among the degrees of satisfaction for the fuzzy goal and for the storage capacities and injectivities. Eq(2) denotes the constraint for the fuzzy goal, while Eq(3) and Eq(4) are the constraints for the degrees of satisfaction for the capacities and injectivities. The overall degree of dissatisfaction, β, is the maximum among the degrees of dissatisfaction of the storage capacities and injectivities which are represented as constraints in Eq(5) and Eq(6). Then, Eq(7) and Eq(8) show that the overall degree of indeterminacy is the maximum among degrees of indeterminacy for storage capacities and injectivities. The parameters *TE* and *TI* in Eq(5) to Eq(8) are the risk tolerance parameters towards dissatisfaction and indeterminacy. Eq(9) denotes the estimated capacity, C_j to be greater than the sum of CO_2 stored in a particular sink while Eq(10) denotes the estimated injectivity to be greater than the sum of the CO_2 flow rate injected. Both of these estimates are bounded between maximum and minimum values as shown in Eq(11) and Eq(12) for capacity and injectivity. Eq(13) represents the constraints of CO_2 flow rate from source *i* to sink *j*. Eq(14) denotes that a particular source is only connected to one sink. Lastly, Eq(15) and Eq(16) provide the nature of the decision variables. The optimization model is implemented in AIMMS with a built-in CPLEX solver in a PC with 3.59 GHz of processor and 16Gb of RAM. The case study that will be presented in the following section has a negligible computational time.

4. Case study

To illustrate the model, a case study adapted from Tapia et al. (2014) is used. The case study consists of five CO_2 sources which are based on fossil fuel-based power plants in Region IVA in the Philippines and one offshore geological reservoir. These power plants can be retrofitted with CO_2 capture technologies at a given range of operating capacities as shown in Table 1. The capacity of the geological sink is assumed to be neutrosophic in nature with capacity as a neutrosophic triplet [150, 200, 300] Mt and an injectivity of [15, 18, 23] Mt/y. The lower bound of the triplet represents the most conservative estimate of the storage characteristics while the upper bound is the most optimistic. The middle value represents the most accurate estimate that can be obtained through repeated measurements or estimation of the geological reservoir. A total of 305 Mt of CO_2 is capturable from all CO_2 sources.

Table 1: CO_2 source data for the case study

Source	Minimum Flow Rate (F_i^L)	Minimum Flow Rate (F_i^U, Mt/y)	Operating Life (ΔT_i, y)	Maximum Capturable CO_2 (Mt)
Source 1	3.20	6.40	11	70.4
Source 2	1.35	3.00	16	48.0
Source 3	0.90	1.50	13	19.5
Source 4	2.88	3.60	13	46.8
Source 5	4.50	6.00	20	120

Solving the model using the case study above yields a model with 34 constraints and 19 variables. A summary of the results in different decision environments is shown in Table 2. Note that the model can be adjusted to these decision environments by adjusting the expert risk parameters *TE* and *TI*. A fuzzy decision environment is set when *TE=1* and *TI=1* while an intuitionistic fuzzy decision environment is set when *TE*=0 and *TI=1*. Based on the results, the most conservative solution is when the decision environment is intuitionistic fuzzy where the total CO_2 stored is equal to the minimum estimate of the storage. This result is due to the nature of the membership and non-membership components of the storage characteristics to push the solution towards minimum risks of overstorage. For the fuzzy decision scenario, a compromise solution is achieved by balancing both fuzzy objectives and fuzzy storage characteristics. Optimizing in this condition results in a solution where 89 % of the total capturable CO_2 is stored in the geological sink. In the scenario where the risk tolerance is at the lowest, 73 % of the total capturable CO_2 is stored in the geological sink. In this case, the optimal solution is less optimistic than in the fuzzy case but more optimistic than in the neutrosophic case. In all cases, Source 5 contributes the highest to the stored CO_2 ranging from 103 Mt to 120 Mt. Source 1 shows consistency in the amount of CO_2 stored in all three decision environments. However, it is possible that both sources 2 and 4 may not be connected to the geological reservoir when the most conservative solution is chosen to be implemented. These insights are useful in implementing large-scale CCS networks as the risks associated with storage characteristics may be perceived differently from one expert to another.

Table 2: Optimal solution for the case study under different decision environments

Source	Total CO_2 captured and stored (Mt)		
	Fuzzy (*TE=1* and *TI=1*)	Intuitionistic Fuzzy (*TE=0* and *TI=1*)	Neutrosophic (*TE=0* and *TI=0*)
Source 1	37.67	35.20	35.20
Source 2	48.00	0.00	21.60
Source 3	19.50	11.70	11.70
Source 4	46.80	0.00	37.44
Source 5	120.0	103.1	115.11
Total	271.97	150.0	221.05

A sensitivity analysis is performed by varying the expert risk parameters and observing its effect on the total CO_2 captured and stored of the system. Figure 2 shows the results as a heat map for different pairs of falsity and indeterminacy tolerance levels. Based on the results, the optimistic solution can be found at high levels of falsity and indeterminacy tolerance levels where the total CO_2 stored ranges from 266 to 272 Mt. In most cases, the total CO_2 captured and stored is at least 200 Mt, especially at high falsity tolerance levels. This behavior is due to the model choosing to utilize the storage site at its most accurate estimate to minimize the degree of indeterminacy at an optimal level of satisfaction. For high values of indeterminacy tolerance, the model tends to provide a solution where the storage characteristics are estimated at the minimum level. This behavior is due to the less weight given to the accuracy of the storage characteristics estimate but giving more importance to the risk associated with over-estimation. The sensitivity analysis performed generates valuable insights about the risk from different perceptions from an expert.

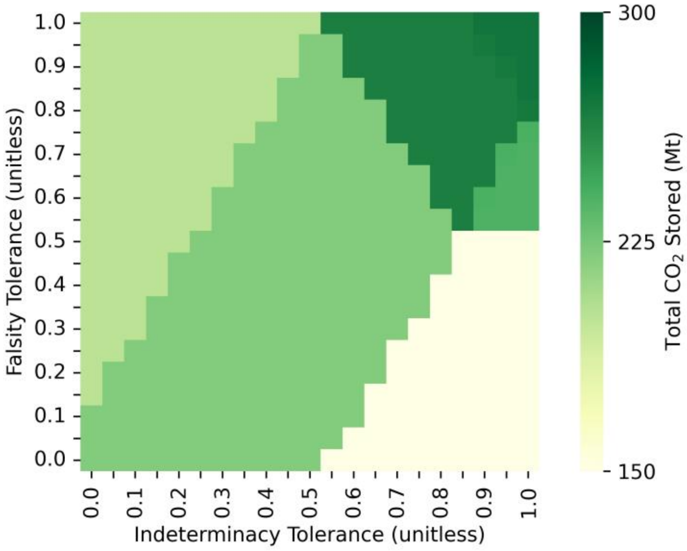

Figure 2: Total CO_2 stored at varying expert risk tolerance levels

5. Conclusions and future work

A neutrosophic linear programming model has been developed for the optimal planning of CCS systems with storage uncertainties. The model captures the risk perception of the expert by adjusting the parameters for tolerance for falsity and indeterminacy. The optimal flow rate levels for each decision environment are determined by using the model. The model can generate insights for managing the risk associated with uncertainty in the characteristics of the storage sites such as capacity and injectivity. In the case study presented, the optimal utilization of the storage sites ranges from 49 % to 89 % of the total capturable CO_2. Future work includes extending the model to incorporate the different availability of sources and sinks. The incorporation of CO_2 utilization and the risks associated with its uncertainty is also subject to future work.

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