Title

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Probability Estimation of CO_2 Leakage Through Faults at Geologic Carbon Sequestration Sites

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Abstract

Leakage of CO_2 and brine along faults at geologic carbon sequestration (GCS) sites is a primary concern for storage integrity. The focus of this study is on the estimation of the probability of leakage along faults or fractures. This leakage probability is controlled by the probability of a connected network of conduits existing at a given site, the probability of this network encountering the CO_2 plume, and the probability of this network intersecting environmental resources that may be impacted by leakage. This work is designed to fit into a risk assessment and certification framework that uses compartments to represent vulnerable resources such as potable groundwater, health and safety, and the near-surface environment. The method we propose includes using percolation theory to estimate the connectivity of the faults, and generating fuzzy rules from discrete fracture network simulations to estimate leakage probability. By this approach, the probability of CO_2 escaping into a compartment for a given system can be inferred from the fuzzy rules. The proposed method provides a quick way of estimating the probability of CO_2 or brine leaking into a compartment. In addition, it provides the uncertainty range of the estimated probability.

Keywords: leakage risk; connectivity of faults and fractures; probability estimation

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1. Introduction

Leakage of CO_2 and brine along faults at geologic carbon sequestration (GCS) sites is a primary concern for storage integrity. Due to (1) the large amount of CO_2 injected and (2) the buoyant nature of CO_2, it is difficult to meet an absolute non-migration-requirement similar to the regulations under the USEPA Underground Injection Control Class I Program during GCS [1]. On the other hand, it is important to recognize that CO_2 is non-hazardous unless concentrations are above certain levels. The key to public acceptance and success of GCS is to address the concerns and demonstrate that the risks of leakage are acceptably small.

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This work is designed to fit into the Certification Framework (CF) for geological CO_2 storage. The overall objective of CF is to develop a simple framework for evaluating leakage risk for certifying operation and abandonment of geological CO_2 storage sites. In the CF, compartments are used to represent vulnerable resources such as potable groundwater, health and safety, and the near-surface environment. The objective of the work is to provide a methodology for calculating P_{leak}, the probability that a CO_2 plume will encounter a system of conduits that is connected to a compartment that may be impacted by leakage and cause potential health, safety and environmental issues.

The fundamental problem addressed by the approach described in this paper is presented graphically in Figure 1. The probability that the CO_2 plume leaks into a compartment through faults or fractures is related to (1) the geometric characteristics of the system of conduits (i.e., distribution and connectivity of faults and fractures) between the storage reservoir and the compartment, and (2) the size and location of the CO_2 plume. For a site (which includes the storage formation and the geological formation above it) to be selected for GCS, some fault and fracture distribution data are expected to be available. However, the information on the conduit system is usually limited and highly uncertain. Moreover, the location and size of the CO_2 plume is also highly uncertain given the uncertain properties of the deep storage reservoir. Therefore, it is a challenge to predict (1) whether the conduits are connected, and if so, (2) the probability that a CO_2 plume will encounter the connected pathways. The proposed method addresses these challenges. The amount of leakage and the impact of leakage on the compartments are not within the scope of this study.

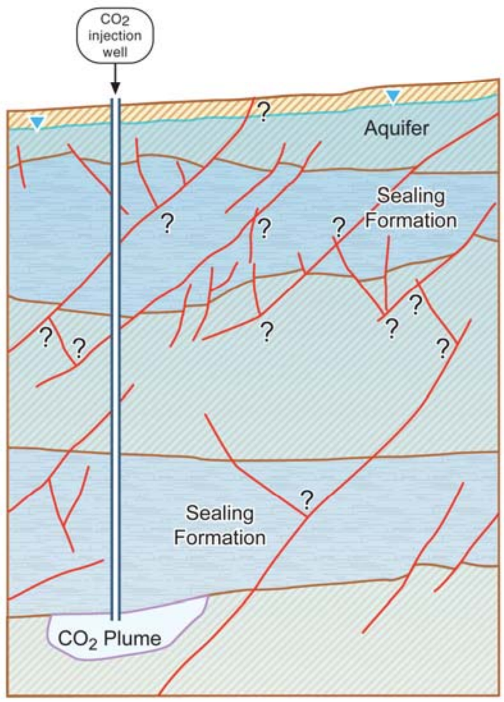

Figure 1. Schematic geologic cross section (not to scale) showing CO_2 injection well, CO_2 plume, reservoir, sealing formation, overlying formations, and potable ground water, along with conductive faults that may or may not intersect as indicated by the question marks.

2. Methodology

The proposed approach includes four steps: (1) estimate a critical value (α_c) for the parameter α, which is related to the density of conduits (faults and fractures), such that when this critical value is reached, the system is on average connected between the storage formation and a compartment; (2) estimate the probability that the CO_2 plume will encounter the connected conduits for a system with $\alpha \geq \alpha_c$, for various distributions of conduits, system sizes and CO_2 plume sizes; (3) construct fuzzy rules that relate information about the conduit system and CO_2 plume size to leakage probability; and (4) for given system characteristics, predict the probability that a CO_2 plume will escape from the storage formation to a compartment through connected conduits.

We make the following assumptions in the study:

- The system under investigation is a square, two-dimensional (2D) cross section with sides of length L.
- Faults/fractures are randomly oriented.
- Faults/fractures considered are conductive.
- Faults/fractures follow a power-law length distribution

2.1. Estimation of critical value α_c

Among different models for describing fault length distributions, the power-law distribution is the most widely used [2, 3, 4]:

$$n(l, L) = \alpha(L) l^{-a} \quad 1)$$

where $n(l, L)dl$ is the number of faults having a length in the range [l, $l+dl$], $\alpha(L)$ is a coefficient of proportionality that reflects fault density and depends on the system size L (assuming a square system with sides of length L), and a is an exponent, which typically varies between 1 and 3. It is obvious from Equation (1) that the power-law distribution contains no characteristic length. This is the key argument for using power laws to describe fault growth processes [5].

Percolation theory [6] has been applied to study the connectivity of fault systems. In percolation theory, a parameter p is used as an average measure of the geometrical properties, generally related to the density of elements, which also provides information on the connectivity of the system. The percolation threshold p_c is defined as the critical p value, below which (on average) the fault system is not connected, while when p is above the critical value p_c, the system is connected. In other words, 50% of the systems at the percolation threshold are connected. Bour and Davy [7] presented an analytical expression for the percolation threshold for a fault system following a power-law length distribution as:

$$p_c(L) = \int_{l_{\min}}^{L} \frac{\alpha_c(L) l^{-a} l^2}{L^2} dl + \int_{L}^{l_{\max}} \alpha_c(L) l^{-a} dl \quad 2)$$

If $l_{max} < L$, the second term on the right-hand side drops out and the first term integrates to l_{max} instead of L.

Bour and Davy [7] also demonstrated that the percolation threshold $p_c(L)$ does not present significant variations with L. For a power-law fault length distribution with any value of a, the computed values of $p_c(L)$ are around 5.6 in two dimensions. By setting p_c to 5.6, an expression for the critical fault density $\alpha_c(L)$ can be obtained. Equation 2) can be normalized with respect to l_{min}, where $\alpha_{cs}(L_s) = \alpha_c(L) l_{\min}^{-a+1}$.

For a given system, we can calculate the critical parameter $\alpha_{cs}(L_s)$ and compare it to the actual parameter $\alpha_s(L_s)$. If the actual density is much smaller than the critical value, we can conclude that the system is not connected and the CO_2 plume will not be able to leak out through the fault system. For systems with $\alpha_s(L_s)$ around or above its critical value, the steps described in Sections 2.2 and 2.3 need to be performed.

2.2. Generation of conduit network to determine P_{leak} for systems with $\alpha_s(L) > \alpha_{cs}(L)$

To estimate the probability that a CO_2 plume escapes through the connected conduits and reaches compartments for a system with $\alpha(L) > \alpha_c(L)$, we vary system parameters to generate discrete fracture networks and perform Monte Carlo simulations. Three types of uncertainty are considered. The first results from our lack of knowledge of the system properties. This uncertainty is considered by using fuzzy-rule-based modeling to propagate the uncertainty of the input parameters in estimating P_{leak}. The second is the uncertainty in the generation of the discrete fracture network itself. Even for systems with the same parameters (e.g., system size and fracture distribution), the generated network could have very different connectivities. This uncertainty is considered by conducting Monte Carlo simulations. The third uncertainty is in the size and location of the CO_2 plume. In the simulation, we will vary CO_2 plume size and using a moving average to consider the uncertain location of the plume.

The parameters varied in the fracture network generation and P_{leak} calculations are the normalized system size L_s, the normalized maximum fracture length $l_{max\ s}$, the exponent a, the ratio of $\alpha_s(L_s)/\alpha_{cs}(L_s)$, and the normalized plume size M_s. The subscript s means they are all normalized values with respect to smallest fault size l_{min}.

For each of the realization of the generated network, the outcome has the following format:

IF L_s=L_1, $l_{max\ s}$=l_1, a=a_1, $\alpha_s(L_s)/\alpha_{cs}(L_s) = r_1$, and M_s=M_1

THEN the probability that a CO_2 plume escapes from the storage reservoir through a connected network of conduit P_{leak} is b.

where L_1, l_1, a_1, r_1 ($r_1 \geq 1$), and M_1 are the numerical values of the varying parameters in the simulation (crisp numerbers), they should cover all possible values considered. b is the calculated P_{leak}.

2.3. Construction of fuzzy rules for calculating P_{leak}

Fuzzy set theory, introduced by Zadeh [8], has been used to deal with approximate (rather than exact) reasoning. In a traditional "if then" statement as shown in equation 3), A_i is a crisp number. In a fuzzy statement, A_i is a fuzzy number that reflects vagueness in the statement. Membership functions of a fuzzy number can have different shapes. Typically, triangular, trapezoid, or Gaussian memberships are used.

$$\textbf{IF} \quad \overbrace{\underbrace{x_1 = A_1}_{1^{st}\ \text{premise}} \ \textbf{AND} \ \underbrace{x_2 = A_2}_{2^{nd}\ \text{premise}} \ \textbf{AND} \ \ldots, \textbf{AND} \ \underbrace{x_K = A_K}_{k^{th}\ \text{premise}}}^{\text{antecedent}}, \ \textbf{then} \quad y = Bi \qquad 3)$$

Fuzzy rules can be used to model systems with imprecise or uncertainty information. These rules can be developed using expert opinions, existing data, and qualitative information. Alternatively, fuzzy rules can be generated through numerical simulations. In our case, we use results from the previous step as a training set to construct fuzzy rules. The counting algorithm or the weighted counting algorithm [9] can be used to construct fuzzy rules.

An example of a fuzzy-rule statement generated from this step is as follows (the numbers in this statement are dimensionless numbers that are normalized with respect the smallest fracture size):

IF $a = (1.1, 1.5, 2.0)$ AND $L_s = (50, 100, 200)$ AND $l_{maxs} = (50, 100, 200)$
AND $r = (0.75, 1.0, 1.25)$ AND $r_p = (0.2, 0.4, 0.6)$
THEN $P_{leak} = (0.01, 0.12, 0.18)$

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where $r_p = M_s/L_s$. Using the centroid method, the final defuzzified P_{leak} for this rule (when it is fulfilled) is 0.1.

2.4. Calculation of P_{leak} for a given system

For a given system, the first step is to calculate $\alpha_{cs}(L_s)$ and compare it to $\alpha_s(L_s)$. If the latter is smaller, P_{leak} = 0. Otherwise, the above fuzzy rules are used to infer P_{leak}. To aggregate fuzzy rules, one option is to use the normalized sum combination method proposed by Bardossy and Duckstein [9]. Another option is to used the Mamdani-type inference system provided by the Matlab Toolbox, which uses a a maximum combination method to aggregate fuzzy rules.

To demonstrate the approach, we use fuzzy rules generated from 2.3 to predict P_{leak} as a function of r_p (CO_2 plume size divided by system size) for a system with a is approximately 1.5, $l_{max\ s}$ is approximately 100, L_s is approximately 100, and a few values of $r = \alpha_s(L_s)/\alpha_{sc}(L_s)$. The final defuzzified P_{leak} are shown in figure 2.

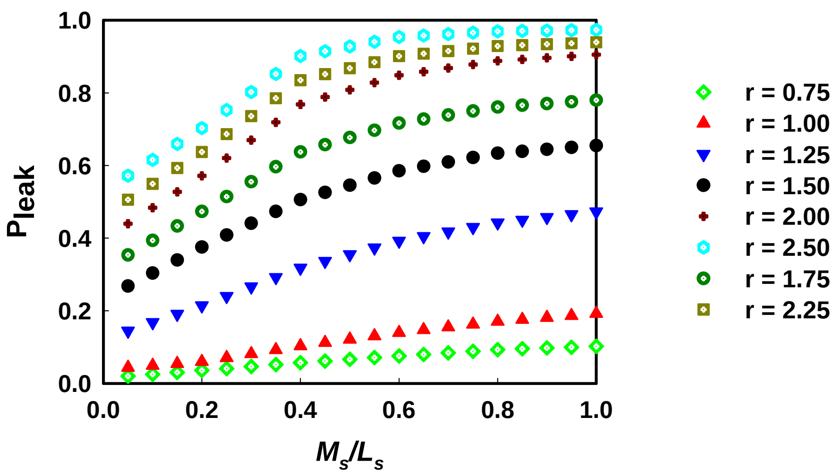

Figure 2. Fuzzy-rule based prediction of P_{leak} as a function of CO_2 plume size for a system with a=1.5, $l_{max\ s}$ = 100, L_s=100, and different values of $r = \alpha_s(L_s)/\alpha_{sc}(L_s)$.

3. Conclusion and Summary

In this paper we presented a method to estimate a limiting factor controlling the probability of CO_2 leakage through a fault or fracture system, namely the probability (P_{leak}) of the plume intersecting a connected network of faults or fractures that also intersects a compartment in which impact may occur. The main computational effort resides in the numerical generation of the fracture networks. However, this only needs to be done once to provide the basis for constructing the fuzzy rules; predictive simulations are then performed very efficiently using these fuzzy rules. The uncertainty of P_{leak} is predicted by propagating the uncertainty in the input parameters. The method can be extended to apply to brine leakage risk by using the size of the pressure perturbation above some cut-off value as the effective plume size.

Acknowledgments
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