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**OPTIMIZATION OF WELL PLACEMENT AND CONTROL
TO MAXIMIZE CO₂ TRAPPING
DURING GEOLOGIC SEQUESTRATION****

1. INTRODUCTION

One of the most promising solution for CCS (carbon capture and storage) is to inject supercritical carbon dioxide into underground saline aquifers due to the large storage capacity [1]. A major concern with CCS in aquifers is the potential for leakage and gas migration outside the trapping zone in the aquifer. Leakage could occur due to loss of integrity of formation cap rock caused by overpressurization of the formation. The consequences of leakage and gas zone spreading in aquifer may include groundwater contamination, ecosystem damage and emission CO₂ into the atmosphere. CCS management should include optimization of injection process. It is preferable that gas should be not trapped only structurally but via other mechanisms. The sequestration process can be separate into two steps. The first step is the operation period when gas is injected into aquifer. It can take up from 10–100 years depending on the size of project. During this phase CO₂ displaces the brine in pore space. A portion of injected gas dissolves into brine, but most of injected gas remains in separate phase. In second step there is no more CO₂ injection. The difference of densities between brine and CO₂ causes the gas migration upwards to the top of geological structure. The cap rock stops the further upward movement – this phenomenon is called structural trapping [2]. This trapping mechanism is not preferable during long term CCS because the CO₂ is still mobile and loss of integrity may cause it to leak from the formation. There is another trapping mechanism which

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is important – residual trapping. In this paper both imbibitions and drainage process occurs simultaneously. Due to hysteresis in the relative permeability curves and residual gas saturation, a significant amount of CO₂ gets trapped in pores as an immobile phase [3–5]. Since the CO₂ trapped by this mechanisms is immobile, this is a preferable trapping mechanism for storing CO₂, due to inability to flow and reach the cap rock. There are another trapping mechanism such as dissolution trapping and mineral trapping [6]. This trapping mechanism is commonly described in literature [7, 8] and not be considered in this paper.

CCS development strategy involves the determination of optimal well placement and control strategy. The problem of well location in heterogeneous formation is complicated because of roughness of objective function surface with multiple local optima. Most studies applied stochastic [9, 10] or derivative-free algorithms like Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) due to avoid becoming trapped in local optima [11, 12]. Well control optimization involves determining time-dependent operating variables like rates or bottom hole pressure in order to optimize and objective function [13].

2. DEFINITION OF THE OPTIMIZATION PROBLEM

In this paper simulation based optimization were applied to reduction the risk of leakage in a storage operation. Optimization entails the determination of optimal placement and control variables for multiple CO₂ injection wells to minimize an objective function. The optimization procedures applied in this paper are noninvasive with respect to flow simulator and do not require gradient formulations.

The optimization problem can be expressed generally as:

$$\min_{u \in \Omega \subset \mathbb{R}^n} J(u) \quad (1)$$

Where J is the objective function to minimize, $u \in \Omega \subset \mathbb{R}^n$ are the optimization variables defining well type, location and injection rates, Ω represents the various bound and inequality constraints defining a convex feasible region for u . The objective function J is taken to be the fraction of total CO₂ injected after 80 years on top layer of aquifer model:

$$J(u) = \frac{C(u)|_{t=T}}{Q|_{t=T}} \quad (2)$$

Where $C(u)$ is gas volume at the top of aquifer at time $t = T$ and Q is total CO₂ injected into aquifer. Simulation time T is assumed to 80 years.

The optimization variables u are divided into two categories, $u = [x, r]$, where x describes the location of N vertical CO₂ injection wells. The r describes the CO₂ injection

rates of each wells over M time intervals. The search space of each variables is presented in Table 1.

Table 1
The search space of variables

Variable	Symbol	Variable size	Units	Bounds
Hell (x) Hell (y)	x	N N	blocks blocks	$[I_1 I_2]$ $[J_1 J_2]$
Injection rates	r	$M \cdot N$	m ³ /day	$[r_{\min} r_{\max}]$

Each injection well is defined by two integer variables, denoted $(x_w^1, x_w^2) \big|_{w \in \{1, \dots, N\}}$ for a total of $2N$ optimization variables. The variables correspond to the (x, y) location of starting point of the well. Wells are prescribed to start and end in the centers of discrete reservoir grid block, these parameters are treated as integer values. The injection rate optimization variables r represent injection rates and are denoted $r_{w,t}$ for $w \in \{1, \dots, N\}$ and $t \in \{1, \dots, M\}$, giving a total of $M \cdot N$ independent control variables. Injection rate are bounded on the interval $[r_{\min}, r_{\max}]$. Total injection rates are bounded by a maximum value, designated $q_{\max}$. In every time step following equality must be satisfy:

$$\sum_{w=1}^N r_w = q_{\max} \quad \forall t \in \{1, \dots, M\} \quad (3)$$

A number of optimization algorithms could be applied to solve the problem described in equation (1). Due to the use a commercial simulator Eclipse that does not provide gradients, gradients-based techniques cannot be applied efficiently. Thus noninvasive gradient-free optimization approaches were applied.

2.1. Optimization methods

Optimization of wells location and control involves a total of $n = 2N + M \cdot N$ optimization variables. In this paper $N = 5$ and $M = 10$ were considered, thus $n = 60$ for combining well placement and control problem and $n = 10$ for placement problem. Problem of this size can be readily addressed using stochastic optimization algorithms.

Particle Swarm Optimization

The PSO algorithm is a based stochastic optimization procedure develop by Kennedy and Eberhardt [14, 15]. The algorithm mimics the social behaviors exhibited by swarms of animals. In the PSO algorithm, a point in the research space is called a particle. The collection of particles in a given iteration is referred to as the swarm.

At each iteration, each particle in the swarm moves to a new position in the research space. Let denote x as a potential solution in the search space of a d – dimensional optimization problem, $x_i(k) = \{x_{i,1}(k), \dots, x_{i,d}(k)\}$ as the position of the i -th particle in iteration k . The new position of particle i in iteration $k + 1$ is computing by adding a velocity, $v_i(k + 1)$, to the current position $x_i(k)$ [16]:

$$x_i(k+1) = x_i(k) + v_i(k+1) \quad (4)$$

where the element of the velocity vector are computed as [16]:

$$v_i(k+1) = \omega \cdot v_i(k) + c_1 \cdot r_1 \cdot (x_i^{pbest}(k) - x_i(k)) + c_2 \cdot r_2 \cdot (x_i^{nbest}(k) - x_i(k)) \quad (5)$$

where ω, c_1, c_2 are weights, r_1 and r_2 are uniformly distributed random variables in range $[0, 1]$, x_i^{pbest} is previous best particle solution and x_i^{nbest} is the best neighborhoods particle position. In this paper authors used $\omega = 0.721$, $c_1 = c_2 = 1.193$. These values were determined from numerical experiment by Clerc [17]. The velocity equation has three components, referred to as a the inertia $\omega \cdot v_i(k)$, cognitive $c_1 \cdot r_1 \cdot (x_i^{pbest}(k) - x_i(k))$ and social $c_2 \cdot r_2 \cdot (x_i^{nbest}(k) - x_i(k))$. In Figure 1 authors shows the velocity computation and solution update in iteration $k + 1$ for a particle in a two-dimensional search space. The inertia component provides a degree of continuity in particle velocity from one iteration to the next, while the cognitive component causes the particle move towards its own previous best position. The social component moves the particle towards the best particle in its neighborhood. These three components perform different role in optimization. The inertia components enables a broad exploration of search space, while cognitive and social components narrow to search towards the promising solution found up to the current iteration.

Fig. 1. Illustration of PSO velocity and particle position

Genetic algorithm

Genetic algorithms (GA) are stochastic search techniques that are based on the theory of natural selection. These algorithms perform a global search by generating randomly set of possible solution (called a population) and then evaluation a fitness function of proposed problem for all the individuals in this population. Individual are then ranked, after which certain operators (selection, crossover and mutation) are applied to generate a new population. The selection operators chooses as parents the individuals with the best objective function value. The selection operator mimics the survival of the fitness evolution in nature. This operators ensures that the population moves towards a better region of the solution space during optimization process. After selection, the crossover operator combines the parents to produce children (next population of individuals). The crossover operator is responsible for probabilistically combining fit individuals with the possibility of producing better children. During mutation, a specific part of individuals is probabilistically modified. The mutation is governed by the mutation rates and gives the GA its exploratory natures because it is possible to move individuals into a new region of search space. GA can explore complex non-smooth search spaces with multiple local optima and may as a results identify promising regions in search space. Another GA feature that can be useful is elitism, where one or more of the best individuals in a population always proceed to the next generation. GA operators is illustrated in Figure 2.

Fig. 2. Illustration of main GA operators

2.2. Simulation model of the aquifer

The simulation model used in this paper is intended to represent an aquifer initially containing only brine, at a temperature of 322 K and initial pressure 11 MPa. The aquifer model is geometrically complex and heterogeneous. Distribution of porosity and permeability in aquifer model is presented in Figure 3. The model has five injection wells open to the reservoir. The location of injection wells as well as injection control strategy were changed during optimization process. Maximum bottom hole pressure are constrained to 22 MPa. The relative permeability were taken from Viking reservoir after reference [18] and presented in Figure 4.

Fig. 3. Distribution of permeability (a) and porosity (b) in aquifer model

Fig. 4. Relative permeability curves for CO₂/brine systems for in-situ conditions for the Viking reservoir core samples

Simulation were performed using CO2STORE option in the ECLIPSE simulator. The simulation in this work are all run fully implicitly, with time steps of 365 days, during injection period and 40 years after injection is completed. At $t = 0$ CO₂ injection is started at the bottom layer (8–10) using wells from I-1 to I-5. CO₂ is injected during 10 years.

3. OPTIMIZATION RESULTS

The optimization were performed for two cases. First case was to optimize location of five injection wells by GA and PSO algorithm for constant injection rate. After that, more efficient algorithm were taken to simultaneous optimization of well placement and control. In case of well placement problem only, constant injection rate was assumed. The injection rate was 300 000 Nm³/d of CO₂ per individual well. Injection time is 10 years and total simulation time is 80 years. In case of join well placement and control problem, injection well rates is bounded by minimum and maximum value – 100 000 and 500 000 Nm³/d of CO₂ per individual well.

3.1. Optimization of well placement

For well placement optimization problem both GA and PSO algorithm were tested. Results of objective function evaluation are presented in Figure 5.

Fig. 5. Progression of objective function evaluation, during well placement optimization

Optimization method perform reduction of CO₂ fraction in top layer from 23.77% to 12.71%. GA and PSO optimization algorithms return the same value, but reduces required number of simulation from over 866 (GA) to 508 (PSO). Every simulation takes about 2 minutes, that PSO algorithm reduces computational time for over 11 hours. CO₂ migrates upward more slowly in the optimized case, and this also provides for more secure storage. Due to over performed PSO, this algorithm was chosen for case with join placement and control optimization.

Distribution of CO₂ in top layer of aquifer is presented in Figures 6 and 7.

Fig. 6. Distribution of CO₂ in top layer of aquifer, after injection period (a) and at the end of simulation (b)

Fig. 7. Distribution of CO₂ in aquifer, after injection period (a) and at the end of simulation (b)

3.2. Simultaneous optimization of well placement and control

For simultaneous well placement and control optimization objective function is presented in Figure 8.

Fig. 8. Progression of objective function evaluation, during joint well placement and control optimization

Optimization method perform reduction of CO_2 fraction in top layer from 23.77% to 12.10%.

Distribution of CO_2 in top layer of aquifer is presented in Figure 9.

Fig. 9. Distribution of CO_2 in top layer of aquifer, after injection period (a) and at the end of simulation (b)

Control strategy for injection wells is presented in Figure 10.

Fig. 10. Control strategy for individual wells during injection period

4. SUMMARY

In presented work authors developed and applied computational procedures for optimization to minimize the risk of CO₂ leakage during long term CCS process. Genetic algorithm (GA) and Particle Swarm Optimization (PSO) algorithms were used to determine the optimal CO₂ injection well locations and time-varying injection rates that minimized the risk of leakage.

Conclusion are as follows:

- in all of the cases, the optimization procedure increased the amount of residual trapping,
- the use of optimization procedure reduce the risks associated with carbon storage operations,
- objective function depends more strongly on the well locations than on the well controls.

Future investigation:

- the impact of additional physics, such as fine-scale heterogeneity, capillary heterogeneity, and mineral trapping, should be investigated to determine their potential effect on optimization,
- use different optimization procedures for the optimization.

REFERENCES

- [1] Gale J.: *Overview of Sources, Potential, Transportation and Geological Distribution of Storage Possibilities*. Presentation at IPCC Workshop on Carbon Capture and Storage, Regina, Canada, 2002.
- [2] Song J., Zhang D.: *Comprehensive review of caprock-sealing mechanisms for geologic carbon sequestration*. *EnvSci& Tech* 47, 2012, pp. 2–22.
- [3] Juanes R., Spiteri E.J., Orr F.M. Jr., Blunt M.J.: *Impact of Relative Permeability Hysteresis on Geological CO₂ Storage*. *Water Resources Research*, vol. 42, 2006, pp. 1–13.
- [4] Kumar A., Noh M., Pope G.A., Sepehrnoori K., Bryant S., Lake L.W.: *Reservoir Simulation of CO₂ Storage in Deep Saline Aquifers*. *SPE Journal*, September 2005, pp. 336–348.
- [5] Mo S., Akervoll I.: *Modeling Long-Term CO₂ Storage in Aquifer with a Black-Oil Reservoir Simulator*. Paper SPE 93951 presented at SPE/EPA/DOE Exploration and Production Environmental Conference, 2005, pp. 1–9.
- [6] Bachu S.: *CO₂ storage in geological media: Role, means, status and barriers to deployment*. *Progress in Energy and Combustion Science*, 34, 2008, pp. 254–273.
- [7] Adamczyk K., Premont-Schwarz M., Pines D., Pines E., Nibbering E.T.J.: *Real-time observation of carbonic acid formation in aqueous solution*. *Science*, 2009, pp. 1690–1694.
- [8] Black J.R., Carroll S.A., Haese R.R.: *Rates of mineral dissolution under CO₂ storage conditions*. *Chemical Geology*, 399, 2015, pp. 134–144.
- [9] Sarma P., Chen W.: *Efficient well placement optimization with gradient-based algorithms and adjoint models*. SPE 112257. In: *SPE Intelligent Energy Conference and Exhibition*, 2008, pp. 1–18.
- [10] Zandvliet M.H.M., van Essen G., Brouwer R., Jansen J.D.: *Adjoint-based well-placement optimization under production constraints*. *SPE Journal*, 13(4), 2008, pp. 392–399.
- [11] Yeten B., Durlowsky L.J., Aziz K.: *Optimization of nonconventional well type, location, and trajectory*. *SPE Journal*, 8, 2003, pp. 200–210.
- [12] Onwunali J., Durlowsky L.J.: *Application of a particle swarm optimization algorithm for determining optimum well location and type*. *Computational Geosciences*, 14(1), 2010, pp. 183–198.
- [13] Jansen J.D., Brouwer D., Naevdal G., Van Kruijsdijk C.: *Closed-loop reservoir management*. *First Break*, 23(1), 2005, pp. 43–48.
- [14] Kennedy J., Eberhardt R.C.: *Particle swarm optimization*. In: *Proceedings of the IEEE International Joint Conference on Neural Networks*, 1995, pp. 1942–1947.
- [15] Eberhardt R.C., Kennedy J.: *A new optimizer using particle swarm theory*. In: *Proceedings of the Sixth International Symposium on Micromachine and Human Science*, 1995, pp. 39–43.

- [16] Eberhardt R.C., Shi Y.: *A modified particle swarm optimizer*. In: Proceedings of the IEEE International Conference on Evolutionary Computation, 1998, pp. 69–73.
- [17] Engelbrecht A.P.: *Fundamentals of Computational Swarm Intelligence*. Wiley, 2005.
- [18] Killough J.E.: *Reservoir simulation with history-dependent saturation functions*. Soc. Pet. Eng. J., 16(1), 1976, pp. 37 – 48.