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Surface Gravity Response of CO_2 Storage in the Johansen Deep Saline Aquifer#

Peizhai Cheng[1*], Pingchuan Dong [1,2], Youheng Zhang [1]

1 China University of Petroleum (Beijing), Beijing, China. 102249

2 State Key Laboratory of Petroleum Resources and Engineering, China University of Petroleum (Beijing), Beijing, China. 102249

(Corresponding Author: 317720733@qq.com)

ABSTRACT

The storage of CO_2 in geological reservoirs is considered one of the most promising solutions to achieve net zero emissions and address the current climate change crisis by 2050. Based on planning CO_2 storage activities, it is necessary to design accurate on-site characteristics and monitoring during the injection and post injection stages to determine reliable and sustainable geological storage. This study involves the evaluation of surface gravity measurements for monitoring CO_2 plumes in the Johansen deep saline aquifer, which is a potential offshore location for CO_2 geological storage. Use available benchmark models and geological information to simulate injection and post injection stages. The gravity response of the surface was calculated based on the estimation model of reservoir density and saturation at different time intervals and injection rates. Forward calculation is achieved by assuming discretization of tetrahedral grids to ensure accurate and detailed reconstruction of complex reservoirs. The results indicate that the gravity anomaly extends radially around the well site, reaching a peak of approximately -15 μ Gal at an injection rate of 60 kg/s. During the post injection period, the gravity map clearly shows that the saturation of saline water around the injection well increases, and the CO_2 plume migrates towards the shallower part of the reservoir.

Keywords: Carbon capture and storage (CCS), CO_2 mass estimation, deep reservoir, gravity monitoring, numerical simulation

1. INTRODUCTION

CO_2 storage in geological reservoirs is recognized as one of the most promising solutions to achieve net zero emissions by 2050 and counteract the current climate change crisis (Krahenbuhl, Martinez, Li, & Flanagan, 2015). At the basis of the planning of CO_2 storage activity, it is necessary to design accurate site characterization and monitoring throughout both the injection and postinjection phases, to determine a sure and long-lasting geological sequestration (Grana, Liu & Ayani, 2020).

In recent decades, geophysical techniques have proved decisive to monitor the dynamics of carbon sequestration sites (Forberg, Grana & Omre, 2021), to validate predictive models and to remotely determine possible leakage patterns of the stored CO_2 (Feng, Zhang, Wohlberg, Symons & Lin, 2021).

Monitoring strategies may include seismic, micro-seismic, gravity, electrical/electromagnetic, well logging, InSAR, and other geophysical methods, each of which has its own advantages and limitations in correctly detecting and imaging the CO_2 stored in the reservoir (Huang & Yang, 2022). Among all, the seismic method has been the main technique used in large-scale carbon capture and storage (CCS) projects. Due to its deep penetration and high spatial resolution, seismic investigations have been conducted both as a baseline setup technique and as a monitoring tool (Gasperikova et al., 2022). Although the seismic method is considered the most effective tool for subsurface monitoring, it is affected by elaborate data processing, considerable time consuming, and high costs. In addition, seismic investigations are often conducted along 2-D profiles, and resolution decreases with depth. This will inevitably limit successful 3-D subsurface modeling and could be challenging especially when dealing with deep geological reservoirs (Jenkins, 2020).

Electrical resistivity tomography (ERT) and electromagnetic (EM) techniques have also been adopted as alternative high-resolution monitoring methods, as injecting CO_2 into the reservoir implies an increase in resistivity. Previous studies have shown that these techniques can successfully track CO_2 plume migration and detect CO_2 leakage in shallow geologic formations. However, both methods are relatively insensitive to the CO_2 plume propagating in horizontal

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resistive layers and do not guarantee a deep enough exploration (Roach, White & Roberts, 2015).

On the other hand, time-lapse gravimetry represents a potential economic, noninvasive, and complementary method to the more traditional seismic monitoring (Schmidt-Hattenberger, Bergmann, Labitzke, Wagner & Rippe, 2016). A time-lapse gravity survey consists of studying at repeated stations the changes in gravity acceleration due to the redistribution of fluids (CO_2 and brine) in the porous medium. By repeating the measurements at different times, it is in fact possible to directly estimate the variation in the mass and density of CO_2, induced by fluid migration and changes in saturation (Appriou, Bonneville, Zhou & Gasperikova, 2020).

Although numerical simulations proved the ability of gravity monitoring to recover the stored CO_2 mass and to assess potential leaks along fractures, it has so far seen limited application in CO_2 storage sites (Jacob, Rohmer & Manceau, 2015).

The first study of time-lapse gravity surveys at an offshore CO_2 storage site was realized at the Sleipner site, in Norway. The repeated gravity measurements allowed estimating gravity anomalies larger than 10 µGal and were decisive in constraining the modeling of the CO_2 density and its rate of dissolution (Appriou & Bonneville, 2022).

The Sleipner case study, as well as numerical simulations, showed that land-based gravity exploration can ensure 1 µGal accuracy with measurements repeatability up to 3 µGal for time-lapse applications. However, for reservoir depth greater than 800 m, it is believed that gravity monitoring at the surface is unlikely to be efficient due to the great distance and the low-density contrast (Gasperikova & Hoversten, 2008). A few of recent studies have also proposed to combine surface (or seafloor) with borehole gravity measurements, so to improve the gravity response magnitude (Wilkinson, Mouli-Castillo, Morgan & Eid, 2017). Drilling boreholes, however, is generally expensive, especially offshore, and can thus be conducted at limited locations at the storage site (Goto, Ishido & Sorai, 2020).

This article focuses on injection scenarios in deep geologic formations. In particular, this study is conducted by performing fluid flow simulations using the benchmark reservoir model of the Johansen formation (JF), a deep offshore saline aquifer located in the Northern North Sea and proposed as a candidate for CO_2 storage by Norwegian authorities (Celaya, Denel, Sun, Araya-Polo & Price, 2023). A couple of recently published articles dealt with the use of gravity monitoring to study fluid migration in the Johansen reservoir. Both aimed at modeling the CO_2 plume using machine learning techniques. Krahenbuhl and Li, however, used only borehole gravity measurements, while Celaya et al. considered a strong injection rate of about 166 kg/s which, according to Bergmo et al., implies an increase in local pressure very close to the estimated safe limit, especially when not employing water production (Nooner et al., 2007).

Therefore, the aim to evaluate, using a realistic reservoir model of JF, the gravity response for a deep saline reservoir using different injection rates, staying within the above pressure limits. In addition, a new efficient tool will be used to assess the stored CO_2 mass, without using any a priori information about the reservoir geometry and the CO_2 plume properties. The numerical simulation results are in strong agreement with the true values of the modeled masses, regardless of the injection rate and the wavelength of the anomaly.

2. MODEL DEFINITION

The JF is a deep saline aquifer characterized by high volumes and suitable pressure regimes, as well as promising geological sealing properties. It is located in the deeper part of the Sognefjord delta on the west coast of Norway field, 60 km offshore of the Mongstad area and below the Troll field, one of the largest gas fields of the North Sea (Alnes, Eiken & Stenvold, 2008).

A benchmark model dataset of the JF was made available by the University of Bergen and the Norwegian Petroleum Directorate, and it is currently accessible under Open Database License by SINTEF. The 3-D geometry was developed from existing seismic and well data and consists of a stack of 11 layers: the first five layers represent the shale (caprock) at the top of the reservoir; layers 6–10 consist of high-permeability sandstones of the JFs, while layer 11 is the lowermost seal represented by low-permeability shales.

The reservoir model is also affected by north–south trending faults which divide the uppermost Troll field into two separate segments. Below the Troll field, at depths ranging from 2200 to 3100 m below sea level, the JF is characterized by an average thickness of 100 m and 100 km of lateral extension (Alnes et al., 2011).

The dataset also includes porosity and permeability values deriving from log and core data of different exploration wells. The average porosity of about 25% suggests that the JF can be suitable for a CO_2 storage volume of at least 160 million tons (Zumberge, Alnes, Eiken, Sasagawa & Stenvold, 2008).

In this work, we performed fluid flow simulation using the numerical modeling simulator COMSOL Multiphysics and considered a restricted portion of the more general model, inspired by previous numerical modeling studies. The model used in this work consists of a single layer with the approximate dimension of 9600 × 8900 m and thickness varying from 90 to 140 m (see Fig. 1). The aforementioned fault causes a progressively increasing northward displacement and uplift of the JF > 400 m.

We selected a proper mesh size to construct the model. The model consists of a fine mesh of about 57 971 tetrahedral elements and of a single injection well located in the central sector and reaching a depth of about 3 km. The geometric model of the JF reservoir is shown in *Fig. 1*, where the red dots represent injection wells.

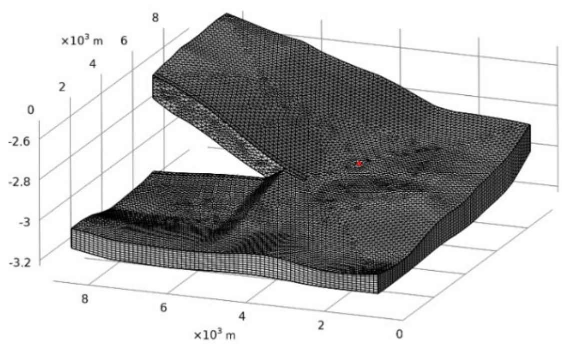

Fig. 1 Reservoir geometry of the JF.

3. CO_2 PLUME SIMULATION

To define the conservation of mass of the Darcy-type immiscible two-phase fluid flow in a porous medium, the governing equations have the form as follows:

$$\frac{\partial}{\partial t}\left(\varphi\rho_p S_p\right)+\nabla\cdot\left(\rho_p \mathbf{u}_p\right)+Q_p=0 \tag{1}$$

where φ is the porosity, ρ_p is the density of the phase p (supercritical CO_2), S_p is the degree of fluid saturation relative to the porosity φ, t is the time, Q_p the source/sink of each phase, and $\boldsymbol{u}_p$ is the flux vector, that is defined by the multiphase form of the Darcy equation as follows:

$$\mathbf{u}_p=-\frac{\mathbf{k}}{\mu_p}\left[\nabla p_p+\rho_p\boldsymbol{\gamma}\right] \tag{2}$$

where **k** is the intrinsic permeability tensor for the solid phase, $\boldsymbol{\gamma}$ is the gravitational acceleration vector, μ_p and P_p are the dynamic viscosity and the pressure of the phase p, respectively. It is also assumed a Brooks and Corey model to include the capillary pressure and relative permeability:

$$S_w+S_o=1 \tag{3}$$

$$P_c=P_o-P_w \tag{4}$$

where P_o, P_w, S_o, and S_w are the pressures and saturations of CO_2 and brine, respectively. P_c is the capillary pressure which can be also expressed as a function of the degree of brine saturation (S_w):

$$P_c\left(S_w\right)=P_{ce}\overline{S}_w^{-1/\lambda} \tag{5}$$

$$\overline{S}_w=\frac{S_w-S_{rw}}{1-S_{ro}-S_{rw}} \tag{6}$$

where P_{ce} is the entry capillary pressure, λ_p is the Brooks – Corey parameter (pore-size distribution), S_{rw} and S_{ro} the residual saturation of the two phases. The relative permeability of the phases is then expressed as follows:

$$k_{rS_w}=\overline{S}_w^{\left(3+\frac{2}{\lambda p}\right)} \tag{7}$$

$$k_{rS_o}=\overline{S}_o^2\left(1-\left(1-\overline{S}_o\right)\right)^{\left(3+\frac{2}{\lambda p}\right)} \tag{8}$$

where

$$\overline{S}_o=\frac{S_o-S_{ro}}{1-S_{ro}-S_{rw}} \tag{9}$$

According to Class et al., we set the initial conditions in the domain assuming a brine-filled reservoir at a hydrostatic pressure distribution, that is dependent on the brine density ρ_w, and a geothermal temperature distribution for a geothermal gradient of 0.03 K/m with an initial temperature of 100 ◦C at 3000 m depth and a pressure gradient of 100 bar/km.

At carbon storage sites, however, the CO_2 is injected and stored as a liquid under supercritical conditions at pressures > 73.9 bar and temperatures > 31.1◦C. We, thus, used the Peng–Robinson equation of state to define the relationship between pressure (P), volume (V), and temperature (T) at the gas, liquid, and supercritical states of CO_2. Therefore, the density of CO_2 is evaluated analytically with respect to the P and T

$$\rho_c=\frac{1}{C}\frac{M_o}{R}\frac{P_o}{T} \tag{10}$$

where C is the fluid compressibility, Mc is the molar weight, and R is the gas constant (0.1889 kJ/kg·K) of CO_2. It should be noted that the density of CO_2 varies significantly with pressure and temperature. At CCS site conditions, CO_2 is injected as a liquid and reaches a supercritical state at pressures greater than 73.9 bar and temperatures higher than 31.1 ◦C.

In the simulation, the lateral boundary conditions are a 0 m hydraulic head, null CO_2 saturation at the sides, and no flow at the top and bottom boundaries. For simplicity, we set sealing properties to the fault faces, since we assume no leakage scenario during the simulation in this study. We set the porosity and permeability to the model domain from the available dataset, which ranges between 16% and 25% and from 25 to 370 mD, respectively. *Fig. 2* and *Fig. 3* respectively show the porosity and permeability distributions used in the reservoir model simulation.

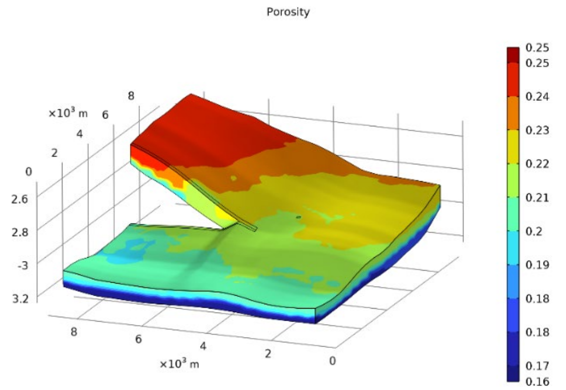

Fig. 2 The porosity distribution used in reservoir modeling simulations.

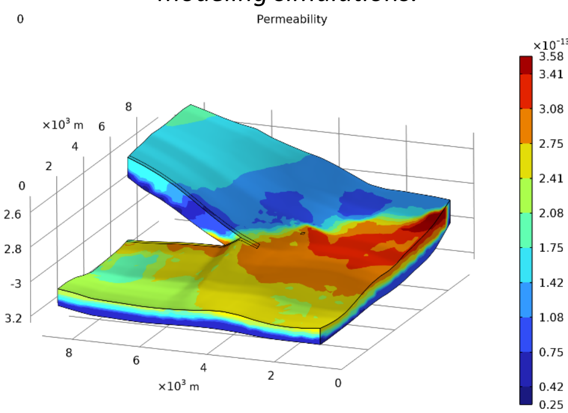

Fig. 3 The permeability distribution used in reservoir models for simulation.

In contrast to other studies, where simulations were performed over large time intervals of hundreds of years, this work aims at studying CO_2 storage over a shorter time interval of 70 years, with a 25-years CO_2 injection followed by 45 years of postinjection monitoring. This would, in fact, represent a more probable condition for a real monitoring activity for CCS purposes. Benchmark studies recommended a constant injection rate of 15 kg/s for a period of 25 years, which however seems to be too much lower with respect to the estimated storage capacity. In this work, we will, instead, investigate the spread of the CO_2 plume by selecting different injection rates. More specifically, we simulate CO_2 injections with constant rates of 15 kg/s (case 1), 30 kg/s (case 2), and 60 kg/s (case 3), which correspond approximately to 0.5, 0.9, and 1.9 Mt/yr, respectively.

In *Fig. 4* and *Fig. 5*, we show the 3-D shape of the CO_2 plume and the CO_2 saturation levels, respectively, after 5, 25, and 70 years from the start of the injection, for each injection rate. In all cases, during the injection period (0–25 years), the CO_2 flowing out of the well bottom displaces the formation brine and rises at the top boundary of the reservoir, spreading radially around the well point. When injecting 15 kg/s (case 1), the plume radius progressively increases from about 900 m, at 5 years [see Fig. 4(a)], to 1.15 km at the end of the injection phase [see Fig. 4(b)]. During the postinjection period (25–70 years), the CO_2 plume gradually migrates northward, along the fault ramp, because of the buoyancy-driven flow [see Fig. 4(c)]. At the last simulation step, the CO_2 plume lengthens reaching a maximum extension of about 3 km. As for case 2 [see Fig. 4(d)–(f)], we observe the plume edge rapidly approaching the fault zone. During the postinjection phase, instead, we observe the CO_2 migrating north-eastward away from the vertical fault [see Fig. 4(e)]. Finally, when assuming an injection rate of 60 kg/s (case 3), the plume diameter greatly increases, flanking to a large part of the fault line at the end of the injection period [see Fig. 4(h)]. The maximum CO_2 saturation is achieved 15 years after the start of the injection and reaches values as high as 76.2% in the near injection well sector for a 60 kg/s injection rate (see *Fig. 5*). We find a maximum value of CO_2 density of about 660 kg/m^3 at 2.9 km of depth.

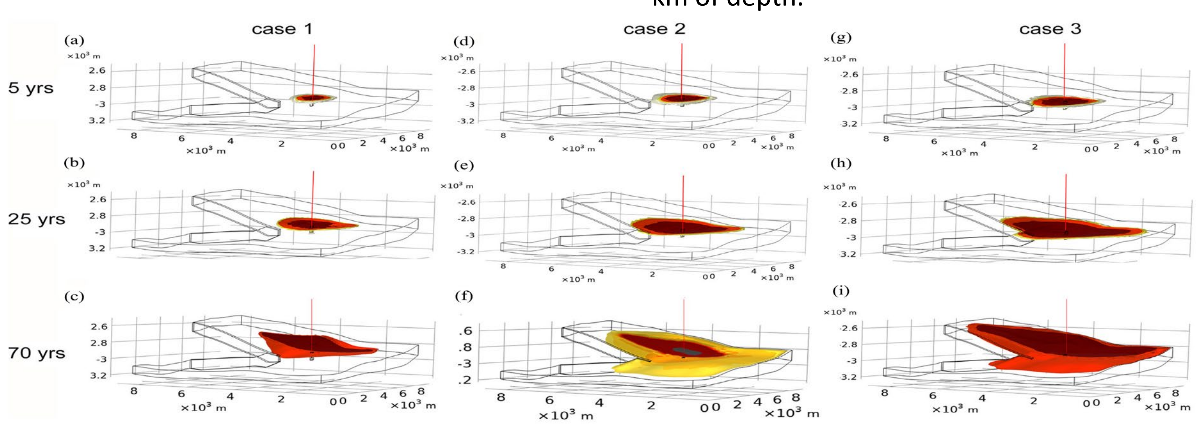

Fig. 4 (a), (d), and (g) CO_2 plume at the first time step (5 years), (b), (e), and (h) at the end of the injection period (25 years), and (c), (f), and (i) at the end of the simulation (70 years) for each injection rate.

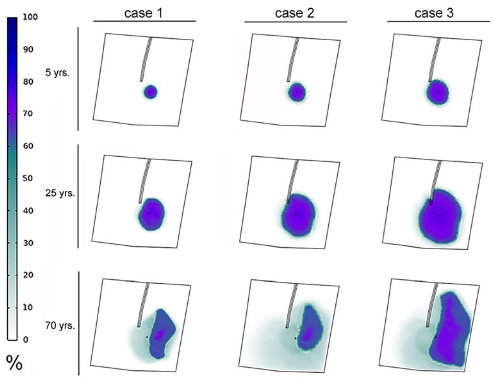

Fig. 5 Variation of the CO_2 plume saturation for each injection rate. The black dot represents the well location.

4. FORWARD GRAVITY CALCULATION

To determine the gravity response versus time, we need to quantify the total wet bulk density variation of a specific volume over a precise time interval. The purpose of time-lapse surveying, however, is to focus only on the changes in fluid distribution within the reservoir at several time periods.

Thus, it can express the wet bulk density variation $\Delta\rho$ as follows:

$$\Delta\rho = \Delta S_{CO_2}\varphi\left(\rho_{CO_2} - \rho_w\right) \tag{11}$$

where ΔS_{CO_2} is the variation in saturation between the baseline and any time step, φ is the porosity, ρ_{CO_2} and ρ_w the densities of CO_2 and brine, respectively. According to other studies, we assume that porosity changes are negligible.

In *Fig. 6*, we show the models of wet bulk density $\Delta\rho$ at 5, 25, and 70 years after the start of the injection for each injection rate. As the brine is displaced by the CO_2, we observe negative bulk density contrasts that progressively expand as the plume grows laterally. The models show a maximum value of $\Delta\rho$ of about −60 kg/m^3 at the center of the plumes, where the CO_2 saturation is found about 75%.

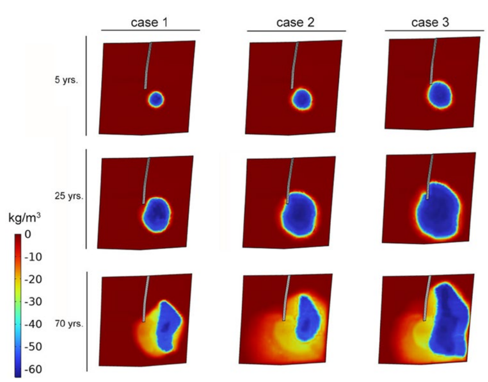

Fig. 6 Models of the bulk density variation for the three injection rates.

5. DISCUSSION AND CONCLUSION

Numerical studies have demonstrated that time-lapse gravity could be successfully applied as a monitoring tool for CCS. Time-lapse gravity monitoring of a carbon storage site involves the estimation of temporal gravity anomalies, which are related to CO_2 injection and associated exclusively with the redistribution of fluids in the reservoir. However, when the site of interest is located at large depths, gravity monitoring could be challenging due to the great distance and the low-density contrast associated with the low rate of mass of CO_2 injected into the reservoir.

This work aimed to assess the feasibility of monitoring the CO_2 plume in a deep saline aquifer such as the JF from surface gravity data and estimating the CO_2 mass stored in the reservoir. We mainly focused on the effect of choosing different injection rates on the gravity response and on monitoring the first decades during and after the injection period, avoiding the wide time intervals commonly considered in other simulation studies. This would be especially important for operators who are likely to be involved in monitoring activities over the next few decades with current instrumental accuracy. This was accomplished by estimating a series of different models of the CO_2 plume in terms of bulk density and saturation variations of the injected gas and the resident brine, by means of multi-physical simulations. In the following, we discuss the main outcomes of the present work.

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