Numerical analysis for characterization of fluid movement in reservoirs (CO$_2$-injection) and overburdens (CO$_2$-leakage) via self-potential measurements

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Contents

1 Introduction ........................................... 1

2 Theoretical Background ................................. 2

2.1 Hydrodynamics ........................................ 2
  2.1.1 Single-Phase Flow ............................... 2
  2.1.2 Multi-Phase Flow ................................ 4

2.2 Electrokinetics ....................................... 5
  2.2.1 Coupling in a Two-Phase System ............... 6

2.3 Code Verification ................................... 8

3 Laboratory Experiments ............................... 9

4 Field Campaign ..................................... 11

5 Numerical Modeling .................................. 13

  5.1 Single-Phase Reservoir Simulations .................. 13
  5.1.1 Thick Reservoir .................................. 13
5.1.2 Parameter Study ......................................................... 16
5.1.3 Thin Reservoir ............................................................ 16
5.1.4 Sealing Caprock .......................................................... 17
5.1.5 Conductive Casing ....................................................... 17
5.1.6 Inverse Modeling and Pathway Identification .................. 19
5.2 Multi-Phase Reservoir Simulations ................................. 21
  5.2.1 Coupling Test ......................................................... 21
  5.2.2 Leaky Well Scenario .................................................. 22
  5.2.3 Aquifer Model .......................................................... 30
  5.2.4 Surface Signal ......................................................... 32
  5.2.5 Well Data .............................................................. 37
  5.2.6 Monte Carlo Inversion ............................................... 38

6 Summary and Conclusion ................................................. 45
  6.1 Single-phase flow ....................................................... 45
  6.2 Multi-phase flow ........................................................ 46
1 Introduction

In response to global climate change due to the emission of greenhouse gases, several schemes have been proposed to inject liquefied CO$_2$ into the earth after separation from, e.g., flue gas. Information on fluid paths, fluid velocity and distribution is vital to estimate the storage capability of a reservoir and to identify potential leakage events. Electric (streaming) self-potential (SP) measurements offer the opportunity to monitor subsurface brine movement directly. The propagation of a CO$_2$ injection front causes SP signals due to the displacement of brine within a storage reservoir.

In this project, we assess the feasibility of SP measurements to monitor fluid movements in the reservoir in response to CO$_2$ injection and in the overburden in response to CO$_2$ leakages. Based on these simulation results, concepts may be developed for monitoring fluid movements in the reservoir and for leakages above the reservoir based on data from shallow boreholes or from the surface.

The electrokinetic effect has been studied extensively in past years, both theoretically and experimentally (Ishido & Mizutani, 1981; Sill, 1983; Revil et al., 1999a,b; Titov et al., 2005). SP measurements have been used already to monitor fluid injection for hydro-fracturing the geothermal reservoir at Soultz-sous-Forêts, France (Darnet et al., 2006). Here, fluid injection in 5000 m depth caused a SP signal of few mV at the surface. In spite of the great depth, the signal was observable which was attributed to the influence of the high conductive metal casing of the injection well. Minsley (2007) reported on numerical modeling and inversion of SP data. Sheffer & Oldenburg (2007) investigated SP signals in groundwater models at field scale.

The influence of saturation under two-phase flow conditions on the coupling between pressure gradient and self-potential gradient were studied in the past by e.g. Guichet et al. (2003); Revil et al. (2007); Linde et al. (2007); Allègre et al. (2012); Mboh et al. (2012). A number of different approaches have been proposed in the literature modeling the saturation-dependency of the coupling coefficient. We implement the approaches of Guichet et al. (2003) and Linde et al. (2007) (see Section 2.2.1). To the best of your knowledge, the latter one is the only approach confirmed by
independent experiments (Mboh et al., 2012). We cannot use the approach of the very recent study of Allègre et al. (2012) because its parameters need to be calibrated on their specific experimental set up which is impossible in our case.

Saunders et al. (2008) studied the potential of streaming potentials for monitoring production in oil fields. They found that SP signals originate at fluid fronts and geologic boundaries and can be measured in wells 100 m away from the front. This allows monitoring the oil displacement front at significant distance. Results for CO$_2$ injection should be comparable to oil production. They found also that the magnitude of the SP depends on salinity, from below 0.1 mV at high salinity (2 mol L$^{-1}$) to 100 mV at low salinity (0.001 mol L$^{-1}$).

2 Theoretical Background

The following equations are implemented into our simulation code SHEMAT-Suite (Rath et al., 2006) which was developed from the SHEMAT code (Clauser, 2003). They allow simulating numerically fluid flow within the reservoir and the corresponding SP signal.

2.1 Hydrodynamics

2.1.1 Single-Phase Flow

First, we study SP signals resulting from saturated, single-phase groundwater flow. Single-phase fluid flow through porous reservoirs is commonly described by Darcy’s law, (Darcy, 1856):

$$v = -\frac{k}{\mu_f}(\nabla p + \rho_f g \nabla z), \quad (1)$$

where $v$ is the specific discharge (or Darcy velocity) (m$^3$ m$^{-2}$ s$^{-1}$), $k$ the hydraulic permeability tensor (m$^2$), $\mu_f$ the fluid dynamic viscosity (Pa s), $\rho_f$ fluid density (kg m$^{-3}$), $g$ gravity (m s$^{-2}$), $p$ the hydraulic pressure (Pa); the vertical coordinate $z$ (m) is assumed positive upwards.

The equation for fluid flow is derived from equation 1 and the equation of continuity, using an
2 THEORETICAL BACKGROUND

Oberbeck-Boussinesq approximation (e.g. Diersch & Kolditz, 2002; Clauser, 2003).

\[ \rho_f (\alpha + \phi \beta) \frac{\partial p}{\partial t} = \nabla \cdot \left[ \rho_f k \frac{\mu_f}{\rho_f} (\nabla p + \rho_f g \nabla z) \right] + W. \]  \hspace{1cm} (2)

Here, \( \phi \) is porosity while \( \alpha \) and \( \beta \) denote the compressibilities (Pa\(^{-1}\)) of solid and fluid phases, respectively. \( W \) is a mass source term (kg m\(^{-3}\) s\(^{-1}\)).

At the moment, we assume constant fluid and rock properties without temperature and pressure dependencies. These properties are adjusted manually to temperature and pressure at depth in each simulated reservoir. In our problems, permeability \( k \) is isotropic and therefore a scalar.

In our applications, groundwater flow driven by self-potential gradients is very small compared to contributions resulting from pressure gradients. Therefore, contributions from self-potential gradients are neglected here (Minsley, 2007).

2.1.1.1 Dimensionless Approach

Flow is controlled by a number of rock and fluid properties. By introducing characteristic length and time, these can be lumped into one single dimensionless number. By calculating this number for a specific problem, our results may be easily scaled to other problems.

As an approximation, we cast equation 2 into an isotropic formulation for constant density in one dimension \( x \):

\[ \rho_f (\alpha + \phi \beta) \frac{\partial p}{\partial t} = \rho_f k \frac{\mu_f}{\rho_f} \frac{\partial^2 p}{\partial x^2}. \]  \hspace{1cm} (3)

As a result, there is no free convection term in the equation any more. We also assume that our flow is free of sources.

Now we introduce now a reference pressure \( p_0 \), a characteristic time \( T \) and a characteristic length \( L \) describing the distance between injection and model boundary.

This way, we can write equation 3 in terms of relative pressure \( p^* \), distance \( x^* \), and time \( t^* \):

\[ p^* = \frac{p - p_0}{p_0}, x^* = \frac{x - L}{L}, t^* = \frac{t - T}{T}. \]  \hspace{1cm} (4)
Now, with hydraulic diffusivity $D = \frac{k}{\mu_f(\alpha + \phi_3)}$ (m$^2$ s$^{-1}$), equation 3 becomes:

$$\frac{\partial p^*}{\partial t^*} - \frac{DT}{L^2} \frac{\partial^2 p^*}{\partial x^*^2} = 0. \quad (5)$$

The non-dimensional coefficient in equation 5 is the mass-transfer Fourier number $Fo = \frac{DT}{L^2}$ which characterizes the flow problem. The characteristic time scale $T$, which cannot be defined easily, is eliminated using the injection rate $W = \frac{ML^2}{T}$ and reservoir thickness $M$, yielding:

$$Fo = \frac{DM}{W}. \quad (6)$$

The Fourier number is defined for single-phase problems only.

### 2.1.2 Multi-Phase Flow

For modeling CO$_2$ injection, a multi-phase module is required for SHEMAT-Suite. This was implemented and tested successfully on synthetic small-scale 3D problems ($\sim 20,000$ grid cells). Here, the flow equations for two phases are (Büsing et al., 2012):

For the wetting phase:

$$\phi \frac{\partial (\rho_f (1 - S_n))}{\partial t} = \nabla \cdot \left[ \rho_f \left( k_{rf} \frac{k}{\mu_f} \nabla p_f + \rho_f g \nabla z \right) \right] + W_f \quad (6)$$

And for the non-wetting phase:

$$\phi \frac{\partial (\rho_n S_n)}{\partial t} = \nabla \cdot \left[ \rho_n \left( k_{rn} \frac{k}{\mu_n} \nabla (p_c + p_f) + \rho_n g \nabla z \right) \right] + W_n. \quad (7)$$

where, $f$ and $n$ indicate fluid (wetting, here: brine) and non-wetting (here: CO$_2$) phases, respectively. $S$ denotes saturation (-) with $S_f + S_n = 1$ and $p_c$ is the capillary pressure relating the pressures in the two phases: $p_c(S_f) = p_n + p_f$. $k_{rf}$ and $k_{rn}$ are the relative permeabilities for the wetting and non-wetting phases, respectively.

The model of Brooks & Corey (1964) is used to describe the permeability and capillary pressure of partially water-saturated rocks:

$$k_{rf} = S_c^{2+\lambda}, \quad (8)$$
2 THEORETICAL BACKGROUND

\[ k_{rn} = (1 - S_e)^2(1 - \frac{2 + \lambda}{\lambda}) , \]  

(9)

\[ p_e = p_d S_e^{-1/\lambda} . \]  

(10)

The parameters in the Brooks-Corey equations are displacement pressure \( p_d \) and pore size distribution index \( \lambda \). For this study, we assume \( \lambda = 2 \) as a typical value. \( S_e \) is effective saturation:

\[ S_e = S_f - S_{fr} \]  

(11)

with residual saturations \( S_{fr} \) and \( S_{nr} \).

The flow equations are solved using exact Jacobians in an implicit Newton method. More details about the multi-phase module can be found in Büsing et al. (2012).

The use of the multi-phase flow module is limited, at the moment, to small problems as the numerical solver cannot handle large reservoir models (~ 500,000 grid cells). Therefore, we focus on large-scale single-phase and small-scale two-phase flow simulations.

2.2 Electrokinetics

The global SP field results from a sum of different electrical current density sources (Allègre et al., 2012). In the absence of a concentration gradient and at constant temperature, the total electrical current density \( J \) (A m\(^{-2}\)) can be written as sum of conduction current density \( j_d \) and streaming current density \( j_s \).

\[ j = j_d + j_s . \]  

(12)

Self-potentials arise in the presence of an electrical double layer at the solid-fluid interface in porous media and result in a streaming current \( j_s = \sigma_b C \nabla P \) when charges moved in response to a pressure gradient. In contrast, the conduction current \( j_d = -\sigma_b \nabla U \) given by Ohm’s law results from a potential gradient. Here, \( \sigma_b \) is the bulk electrical conductivity (S m\(^{-1}\)) and \( C \) is the SP
2 THEORETICAL BACKGROUND

coupling coefficient (V Pa$^{-1}$). Thus, equation 12 becomes:

\[ J = -\sigma_b \nabla U + \sigma_b C (\nabla P + \rho_f g \nabla z). \]  \hspace{1cm} (13)

In the literature, the coupling coefficient is usually given as by \( L \) (A Pa$^{-1}$ m$^{-1}$):

\[ L = \sigma_b C. \]  \hspace{1cm} (14)

Without external sources, the conservation of total current density yields:

\[ \nabla \cdot j = 0. \]  \hspace{1cm} (15)

In case of a homogeneous medium without any contrast in electrical conductivity, at constant
density, and in steady-state, equation 15 implies:

\[ \nabla^2 U = C \nabla^2 P. \]  \hspace{1cm} (16)

Thus, self-potential differences result from pressure differences linearly with respect to the
coupling coefficient:

\[ C = \frac{\Delta U}{\Delta P}. \]  \hspace{1cm} (17)

As self-potentials in this study arise only from fluid movement, we use the terms streaming-
potential and self-potential synonymously.

2.2.1 Coupling in a Two-Phase System

Saturation influences the coupling coefficient in a two-phase system. CO$_2$ (gaseous and supercriti-
cal) is non-polar, but due to the position of molecules, it behaves as an electrically non-conducting
quadrupole without dipole moment. The single-phase coupling coefficient can be applied only for
the water phase within a water-CO$_2$ multi-phase system. For the two-phase system, an effective
coupling coefficient \( C_{eff} \) can be defined instead of the coupling coefficient \( C \) in the equations above. There are many approaches for defining \( C_{eff} \) correctly. In our study, we implemented the approaches of Guichet et al. (2003) and Linde et al. (2007), which modify the coupling coefficient under fully water-saturated conditions \( C_{sat} \). Guichet et al. (2003) proposed

\[
C_{eff} = C_{sat} \cdot S_e .
\]  

In contrast, Linde et al. (2007) chose:

\[
C_{eff} = C_{sat} \cdot \frac{k_{rf}}{S_f^{n+1}} .
\]  

with Archies’s saturation exponent \( n \) (Archie, 1942). Here, we assume \( n \) equal to 1.6 as typical value. We performed numerical experiments exploring the difference between the two approaches regarding our injection scenarios. Applying equation 18 results in by \( \sim 20\% \) smaller absolute self-potentials than equation 19.

Recently, Mboh et al. (2012) confirmed the approach of Linde et al. (2007). Therefore, and for lack of additional experimental data for studying the effective coupling coefficient, we use the approach of Linde et al. (2007) here.

In addition, the effective bulk electric conductivity \( \sigma_{b,eff} \) in unsaturated conditions needs to be taken into account. Therefore, we follow Linde et al. (2007) again setting

\[
\sigma_{b,eff} = \sigma_{b,sat} \cdot S_f^n ,
\]  

where \( \sigma_{b,sat} \) is the fully water-saturated electrical conductivity.

Combining equation 19 and equation 20 then yields the effective coupling coefficient \( L_{eff} \)

\[
L_{eff} = \sigma_{b,eff} C_{eff} = L_{sat} \cdot \frac{k_{rf}}{S_f} .
\]  

Figures 1 (a) and (b) show the magnitudes of \( C \) and \( L \), respectively, with saturation of the
2 THEORETICAL BACKGROUND

non-wetting phase. They vary from $C_{sat}$ and $L_{sat}$ (at full water-saturation) to zero at residual water saturation.

2.3 Code Verification

For verifying the SP module, we use the Thiem problem (Bear, 1979), a simple single-phase flow drawdown problem. The steady-state hydraulic head is computed corresponding to pumping an isotropic, homogeneous, confined, and laterally unbound aquifer by a single well. The computed results are compared to an analytical solution (Bear, 1979):

$$U = \frac{L_h W \mu f}{\sigma_b 2\pi dk} \ln \frac{r}{R},$$

where $r$ is the radial distance from the well (m), $R = 1400$ m the distance between well and model boundary (m) (where the hydraulic head is assumed to be zero), $d = 22$ m the aquifer thickness, and $W$ the pumping rate ($m^3 s^{-1}$). As we evaluate drawdown (m) and not pressure (Pa), the coupling coefficient $L$ (A Pa$^{-1}$ m$^{-1}$) depending on pressure needs to be re-formulated in terms of head: $L_h = \frac{L}{\rho g}$ (A m$^{-2}$). Assumed values for the model parameters are given in Table 1.

We use a grid of $141 \times 141$ cells for simulating the hydraulic head and the corresponding SP.
3 LABORATORY EXPERIMENTS

Table 1: Assumed properties for the Thiem problem.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$W$</td>
<td>-0.034 m$^3$ s$^{-1}$</td>
</tr>
<tr>
<td>$R$</td>
<td>1400 m</td>
</tr>
<tr>
<td>$d$</td>
<td>22 m</td>
</tr>
<tr>
<td>$k$</td>
<td>$1.8 \times 10^{-10}$ m$^2$</td>
</tr>
<tr>
<td>$L$</td>
<td>$1.5 \times 10^{-10}$ A Pa$^{-1}$ m$^{-1}$</td>
</tr>
<tr>
<td>$\sigma_b$</td>
<td>0.018 m$^{-1}$</td>
</tr>
</tbody>
</table>

Figure 2 shows the numerical result and the analytical solution which agree well.

Additionally, we simulated the test models Minsley (2007) with our code. The results are in good agreement. Thus, the SP module is verified successfully and used for the further modeling.

3 Laboratory Experiments

While coupling coefficient values are taken from the literature currently, laboratory studies are crucial for more realistic predictions of SP signals based on numerical simulations. To this end we set up an experimental apparatus as shown in Figure 3. We pump saline water through a Teflon-coated sample at fixed flow rates. The main experimental components are non-polarizable electrodes for measuring the streaming potential and pressure transducers for recording the fluid pressure gradient across the sample. Flow through the sample is generated by a pump allowing a constant flow rate or constant pressure.

While the SP signal varies with flow rate, water salinity, and temperature, the electrical potential across the sample must be exclusively due to the applied hydraulic gradient for accurately characterizing the streaming potential coupling coefficient. Therefore, salinity and temperature were controlled and kept constant during the experiment.

We see linear relation between flow rate and streaming potential (Figure 4). The voltage signal we measured is at the order of some $\mu$V to mV.

More information on measurements and results are given in Triebe & Klitzsch (2013).
Figure 2: Simulated self potential (SP) for the Thiem problem compared to the analytical solution.

Figure 3: Setup of the laboratory apparatus: Scheme (a) and photo (b) showing a sandstone core coated in a black shrink tube with teflon casing installed onto each end of the plug. Also shown are three connections for the pump, the electrodes and the pressure transducer.
4 Field Campaign

Field experiments were performed for validating the modeling approach at a later stage. Leakage scenarios were studied at a site of natural CO\textsubscript{2} source for lack of real sequestration site data. The site is located in the south of the Eifel mountains in Western Germany, where several CO\textsubscript{2} sources are found which are associated with former volcanic activity. We measured in the D¨orbacher forest, located in the south of Heckenmünster, Rheinland-Pfalz. The field work consisted of geoelectrical and SP measurements and of CO\textsubscript{2} concentrations. An area of 16 m × 64 m was monitored at a CO\textsubscript{2} source site and 10 m × 50 m at a H\textsubscript{2}S source site. Measurements used unpolarizable Pb-Pb/Cl-electrodes. One of the electrodes was used as a reference electrode while the other one records the potential difference at a distance of 2 m and 1 m (near the source). Figure 5 shows positive SP values near the CO\textsubscript{2} source caused by an upward flow. Similar results are shown in Figure 6 with positive SP values near the H\textsubscript{2}S source and along a lineament in y-direction which may be associated with downward fluid flow movement along a slope.

![Diagram](image.png)

Figure 4: Relation between flow through porous sandstone and streaming potential with three different pump rates. The variability inside the three stages results from low temperature difference. We used Ag/AgCl electrodes for these measurements.
Figure 5: SP measurements (contour colors and dotted lines), CO$_2$ source (circle).

Figure 6: SP measurements (contour colors and dotted lines), H$_2$S source (circle).
5 Numerical Modeling

First, we concentrate on single-phase flow simulations for gaining experience in simulating SP signals. Moreover, this is of interest for instance for SP studies in geothermal reservoirs. Afterwards, we show multi-phase flow modeling.

5.1 Single-Phase Reservoir Simulations

For investigating the SP signals caused by fluid injection into a sandstone reservoir, we set up a numerical model (4 km \( \times \) 4 km \( \times \) 700 m) which consists of \( \sim \) 370 000 grid cells, with varying resolution of 20 m to 640 m in the horizontal directions and 20 m in vertical direction. The model and the numerical grid are shown in Figure 7. The permeable reservoir is located at a depth of 600 m under a nearly impermeable overburden.

Model parameters are listed in Table 2. Fluid properties are constant, with a density of 995 kg m\(^{-3}\), a dynamic viscosity \(0.8 \times 10^{-3}\) Pa s, and a compressibility of 4179 Pa\(^{-1}\).

Pressure on all model boundaries is kept constant at initial values to allow fluid flow through the boundaries. The potential shows radial-symmetry (Figure 7). Assuming positive coupling coefficients, injection and production are associated with negative and positive voltage signals, respectively.

We study the influence of reservoir thickness, injection rate, permeability, porosity, electrical conductivity, coupling coefficient, and reservoir depth on the signal, in particular the signal at the surface.

5.1.1 Thick Reservoir

For scenario S1 (Table 2), Figure 8(a) shows the potential at a depth of 650 m with respect to the horizontal distance from the injection point at different times after start of injection. The horizontal signal increases with time, which results from the transient propagation of the front within the reservoir. Figure 8(b) illustrates the variation of the SP signal with vertical distance from the injection point. The signal increases with time also in the vertical direction, even though
**Figure 7:** SP signal (epot) inside sandstone reservoir within subsurface model and fracture zone (not used) after two years of injection, as well as numerical grid.

**Table 2:** Properties of the 3D model for different Scenarios S1 – S3. Note that all results need to be interpreted with respect to the assumed coupling coefficient.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reservoir permeability</td>
<td>$10^{-12}$ m$^2$</td>
<td>$10^{-12}$ m$^2$</td>
<td>$10^{-12}$ m$^2$</td>
</tr>
<tr>
<td>Overburden permeability</td>
<td>$10^{-16}$ m$^2$</td>
<td>$10^{-16}$ m$^2$</td>
<td>$10^{-21}$ m$^2$</td>
</tr>
<tr>
<td>Fracture zone permeability</td>
<td>$10^{-16}$ m$^2$</td>
<td>$10^{-16}$ m$^2$</td>
<td>$10^{-21}$ m$^2$</td>
</tr>
<tr>
<td>Reservoir porosity</td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
</tr>
<tr>
<td>Overburden porosity</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>Fracture zone porosity</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>Reservoir thickness</td>
<td>100 m</td>
<td>10 m</td>
<td>100 m</td>
</tr>
<tr>
<td>Fourier number</td>
<td>$1.3 \times 10^4$</td>
<td>$1.3 \times 10^3$</td>
<td>$1.3 \times 10^4$</td>
</tr>
<tr>
<td>Bulk electrical conductivity</td>
<td>0.01 S m$^{-1}$</td>
<td>0.01 S m$^{-1}$</td>
<td>0.01 S m$^{-1}$</td>
</tr>
<tr>
<td>SP coupling coefficient</td>
<td>$1.5 \times 10^{-9}$ A Pa$^{-1}$ m$^{-1}$</td>
<td>$1.5 \times 10^{-9}$ A Pa$^{-1}$ m$^{-1}$</td>
<td>0</td>
</tr>
<tr>
<td>Injection rate</td>
<td>75 L s$^{-1}$</td>
<td>75 L s$^{-1}$</td>
<td>75 L s$^{-1}$</td>
</tr>
<tr>
<td>Simulation time</td>
<td>40 a</td>
<td>2 a</td>
<td>2 a</td>
</tr>
<tr>
<td>Time step</td>
<td>3.65 days</td>
<td>3.0 hours</td>
<td>3.65 days</td>
</tr>
</tbody>
</table>
Darcy flow rates are much smaller in this dimension due to the overburden with permeability four orders of magnitude lower than reservoir permeability. Still, there is non-negligible filtration velocity in the overburden (see Figure 8(c)). The increasing absolute value of the signal with time is shown in Figure 9. After 12 years, a steady-state is reached and the signal stays constant.
5 NUMERICAL MODELING

5.1.2 Parameter Study

A sensitivity study of the surface SP signal with respect to various reservoir parameters yielded the following results:

(i) As expected, the SP signal at the surface increases linearly with the injection rate. It scales with pressure at the injection point which, according to Darcy’s law, depends linearly on the injection rate. (ii) For the same reason, the SP signal also scales linearly with reservoir permeability. (iii) In contrast, the SP signal does not carry with reservoir porosity, as long as a constant bulk electric conductivity can be assumed. (iv) The SP signal varies with the inverse of bulk electric conductivity of the reservoir. This becomes clear from equation 22 when understanding the injection well as a point source of the SP signal. (v) The signal increases linearly with the coupling coefficient of the reservoir. All of these findings confirm the expected results.

5.1.3 Thin Reservoir

In scenario S2, a thin reservoir corresponds to greater filtration velocities due to conversation of mass. The corresponding larger vertical SP signals are shown in Figure 10(a) in comparison to signals from scenario S1. The SP signal at the surface increases by a factor of about five for a decrease of thickness by a factor of ten. It reaches steady-state after an injection period of about \( \sim 15 \) years.

Additional simulations showed that, in this case, reservoir pressure depends strongly on reservoir thickness (in an non-linear way) up to a reservoir thickness of 100 m. For greater thicknesses reservoir pressure and SP signals at the surface are influenced only little by reservoir thickness.

In order to provide generic findings independently from specific geometries and in order to allow transferring our results to other cases, we also provide the curves in the figure with respect to non-dimensional depth and Fourier number (Figure 10(b)). The large Fourier numbers (see Section 2.1.1.1) here show that the ratio between transported mass to stored mass is \( 10^3 - 10^4 \).
5.1.4 Sealing Caprock

Even without a permeable overburden, signals should be observable at a depth of 300 m. This is illustrated in Figure 11 for scenario S3. For the given reservoir geometry, coupling coefficient, conductivity, permeability, and injection rate, the signal is in the range of 0.3 mV at the surface. Therefore, according to Saunders et al. (2008), it should be observable at the surface.

In this case, the signal shows no time-dependency because of the vanishing coupling coefficient in the overburden. Note that for avoiding spurious modeling results, the coupling coefficient of the caprock should be reduced with permeability \( k \). This follows from the approach of Linde et al. (2007) for sedimentary rock:

\[
C(k) = \frac{Q_V k}{\mu_f \sigma_b},
\]

where \( Q_V \) is the excess charge in the water phase per unit pore volume (C m\(^{-3}\)). Thus, \( L \) becomes \( L(k) \):

\[
L(k) = \frac{Q_V k}{\mu_f}.
\]

Note that \( Q_V \) also depends on permeability (Jardani & Revil, 2009):

\[
\log_{10} Q_V = -9.2 - 0.82 \log_{10} k.
\]

Similar simulations concerning reservoirs at a depth of 2000 m yield signals in the order of \( 10^{-4} \) mV. As long as rock properties remain in a reasonable range and the casing does not amplify the signal, reservoir monitoring will not be possible for this deep case using potential measurements at the surface.

5.1.5 Conductive Casing

In the past, the influence of a conductive casing on the potential was observed at the Enhanced Geothermal System (EGS) at Soultz-sous-Forêts, France, (Darnet et al., 2006) and modeled already by our group (Rath, 2006; Rath & Klitzsch, 2007). Conductive metal casings of wells
Figure 9: Scenario S1: Surface SP signal at the borehole location after 40 years of injection.

Figure 10: Scenarios S1 and S2: Vertical SP signals for a reservoir thickness of 100 m (S1) and 10 m (S2) after 2 years of injection (a) and comparison between both scenarios with respect to Non-dimensional depth and Fourier numbers Fo (see Section 2.1.1.1) (b). The signals are caused by fluid ascending in the overburden.
affect the SP signal significantly. One the one hand, they disturb the SP signal caused by the flow regime. On the other hand, they may conduct a signal from a depth of 5000 m to the surface and allow measurements of SP signals which otherwise would not be detectable (Darnet et al., 2006).

### 5.1.6 Inverse Modeling and Pathway Identification

As the stochastic tools implemented in SHEMAT-Suite were not compatible with the two-phase flow module so far, we used fluid dominated reservoirs to test the capability of SP data for identifying fluid pathways and their permeability. A paper published on this topic by us (Vogt et al., 2013). In this paper, for simulated reservoir conditions at Soultz-sous-Forêts, France, we generate synthetic streaming-potential observations and study the value of these measurements for estimating permeability in a deep EGS reservoir.

We find that downhole SP monitoring characterizes the near-field (150 m) permeability around deep geothermal injection and production wells during operation. High permeability zones are
indicated by SP data when assuming a coupling coefficient independent of permeability. In this case, the SP signal agrees well with the hydraulic head distribution. With a permeability-dependent coupling, the influence of the production and injection cells does not allow any interpretation, neither for the near nor the far-field permeability. For permeability-dependent coupling as well as independent coupling, Darcy velocity and, hence, possible flow pathways identified by tracer experiments cannot be distinguished uniquely in the far-field from SP data.

SP monitoring at many observation points is usually not possible at great depths where the EGS technique is applied. However, deviated extensions from boreholes may allow observations around the injection and production wells to some degree (Figure 12). Assuming such a situation, stochastic inversion is performed on synthetic data generated for such a configuration. In this case, principal fluid pathways and permeability magnitudes are reproduced by stochastic inversion based on a combined data set of SP and tracer concentration, and even of SP data alone. Regardless of the type of coupling (constant or varying), both approaches yield comparable inversion results as long as SP data from the injection and production cells are excluded. Permeability and pathway geometry are estimated successfully even when based on an incorrectly assumed coupling coefficient, as long as it does not deviate by more than half an order of magnitude from the true value.

For making use of in-situ SP measurements at Soultz or other EGS sites, we recommend performing lab measurements on fractured crystalline rock for obtaining information on magnitude and permeability dependence of the coupling coefficient.

In summary, the use of SP data for estimating fluid pathways in deep geothermal reservoirs provides an alternative to tracer tests as long as deviated well extensions can be used for recording data. In this case, results are comparable with results based on data from tracer experiments. Data recorded at production and injection points should not be considered for inversion since the corresponding large SP signals are dominated by high pressure gradients or flow rates, possibly yielding spurious results. However, as deviated wells are costly, we see no advantage of the use of SP data instead of tracer tests, because permeability is not resolved significantly better by SP.
Figure 12: Positions of monitor points within the model along the wells (a) and from deviated wells (b) to record transient SP data for data assimilation.

SP monitoring is of more use in shallow reservoirs or in reservoirs with two-phase flow, where the displacement front causes an additional SP signal (Saunders et al., 2008).

5.2 Multi-Phase Reservoir Simulations

In the following, we study the capability of SP data interpretation for identifying CO2 front propagation within a storage reservoirs and leakages. Therefore, the influence of partially saturated brine on the signal has to be taken into account.

5.2.1 Coupling Test

Different coupling approaches are possible for partially saturated brine. We choose the approach of Linde et al. (2007) as discussed in Section 2.2.1, assuming the typical values $S_{fr} = 0.3$, $S_{nr} = 0.08$, $p_d = 10^5$ Pa, $n = 1.6$, and $\lambda = 2$. For a small CO2 injection example (not shown), Figure 13 illustrates the absolute values of differences of pressure $|\Delta p|$ (a) and saturation $|\Delta S_n|$ (b) between two time steps 12 m above the injection point.

Obviously increasing pressure and saturation changes increase the SP. Therefore, the CO2 injection displacement front should be observable using SP monitoring. In addition, the SP signal
Figure 13: Multi-phase flow: absolute values for differences in pressure $|\Delta p|$ (a) and saturation $|\Delta S_n|$ (b) between two time steps 12 m above a CO$_2$ injection point.

is observable even before the pressure and saturation signal reach the monitor point. This confirms the results of Saunders et al. (2008), allowing monitoring of the front in significant distance by observation wells.

In total, the SP signal is very small in this case based on the injection rate of 0.05 kg s$^{-1}$ and $L = 1.5 \times 10^{-9}$ A Pa$^{-1}$ m$^{-1}$. In real reservoirs, injection rate and, thus, SP signal are assumed to be larger by a factor of at least 100. Unfortunately, also oscillations of the numerical solutions are visible in Figure 13, complicating the interpretation of the results. Moreover, to interpret results, it is much more useful to study not the total SP signal, but differences of SP signals.

5.2.2 Leaky Well Scenario

We study a leakage scenario where super-critical CO$_2$ flows from a storage aquifer through a leaky well into a second aquifer. For testing whether this leakage can be identified using an SP monitoring array at the surface.

We use an numerical 2D model shown in Figure 14. This model is motivated by the work of Ebigbo et al. (2007) where two aquifers are connected by an leaky well. CO$_2$ is injected for storage in Reservoir 1. At lateral boundaries pressure and saturation are fixed allowing in- and outflow. Top and bottom are isolated. Corresponding material properties are listed in Table 3. The
horizontal grid size is coarse towards the boundaries for accommodating a large model dimension, minimizing boundary effects and the influence of the reference potential.

5.2.2.1 Results

Figure 15 illustrates the CO$_2$ saturation in the model (a) and the corresponding SP signal (b) after 1000 days of injection. Whereas the leakage is clearly visible in the saturation, the SP signal is not easy to interpret. The overall signal is dominated by the pressure gradients in the injection region. Therefore, the SP signal originating at the injection front cannot be easily discriminated. Therefore, in the next sections we study signal differences in order to identify the leakage.
Figure 15: CO$_2$ saturation (a) and corresponding SP signal (b) inside the leaky well model after 1000 days of injection.

5.2.2.2 Differential Surface Signal

In a next step, we compare the SP field with one corresponding to a perfectly sealed well (Figure 16). Evidently, both signals are very different. Thus, an identification of the leakage should be possible based on the difference between both signals. In the real world, the SP signal would be observed only in boreholes or at the surface. Therefore, we focus on surface data here.

Figure 19 illustrates the differential signal at the surface at different times with and without leakage. This approach eliminates the dominating influence of the large pressure gradients near the injection points, enhancing the effect of the leaky well on the SP signal.

Between 10 days and 100 days, the displacement front reaches the leaky well and appears in the upper aquifer (Reservoir 2), as shown in Figure 20. At this time, also a differential signal can be measured at the surface (Figure 19(c)).
Figure 16: CO$_2$ saturation (a) and corresponding SP signal (b) without leaky well after 1000 days of injection.
The amplitude of the signal increases with time as CO$_2$ displaces brine in the aquifer. The maximum is shifted to the right from the center, where the original injection in the lower aquifer (Reservoir 1) takes place, indicating the position of the leakage.

After 400 days, the signal amplitude becomes smaller again (Figure 19(f)). This is due to the saturation depended coupling coefficient (equation 21), which yields a decreasing voltage with increasing saturation of the non-wetting phase. Moreover, the peak’s width increases with time due to the diffusive character of the SP signal propagation.

5.2.2.3 Image Filter

As an alternative, the global signal can be visualized even without using a differential signal. To this end, we apply the ‘unsharp mask’ filter of the Corel Draw software (Figure 21) which makes the leakage visible clearly in the absolute SP signal. However, this can be applied only when an image from a network of monitoring wells is available and not for data recorded at the surface.

5.2.2.4 Dipole Scanning

Most of the time, the subsurface will not be as densely monitored as is required for obtaining an image which the ‘unsharp mask’ filter can be applied (Figure 21). In addition, numerical simulation studies will not be performed in all cases for comparing signals with and without leakage (Figure 19). Dipole measurements can be used for identifying the leakage directly based on monitoring array data. In this method, the voltage differences between pairs of electrodes with equal distance from the injection point are measured as shown in Figure 17. This makes use of the disturbance of symmetry of the problem by the leakage. Without leakage, the voltage difference between the electrodes would vanish. In contrast, the leakage causes a clear signal at the surface above its position at depth as shown for two times (400 days and 1000 days) in Figure 18. The sign of the signal indicates the position of the leakage (+: to the left of the injection well; -: to the right right of the injection well when subtracting the left from the right voltage).
5 NUMERICAL MODELING

Figure 17: Spreading dipole configuration for SP measurements.

Figure 18: Voltage differences between pairs of electrodes configured as shown in Figure 17. The voltage is plotted versus distance of the left model boundary for comparison with Figure 19. The beginning of the red line indicates the position of the injection well.
5 NUMERICAL MODELING

5.2.2.5 Depth Interpolation

As a rule, CO$_2$ storage reservoirs are located at a depth of 800 m and below (Büsing et al., 2012) because there temperature and pressure conditions are compatible with super-critical CO$_2$. This allows storing large amounts of CO$_2$ due to the higher density compared to the CO$_2$ gas. Therefore, the top of the models is at depth of 600 m.

We now estimate the SP signal at the surface for models at a realistic depth. To this end, we assume isotropic and homogeneous bulk electric conductivity $\sigma_b$ in the overburden and that the SP signal originates at a as point source at the leakage position. This yields an equation for the maximum differential voltage $U_{max}$ at surface (Robinson & Coruh, 1988):

$$U_{max} = u' \frac{1}{r}.$$  \hspace{1cm} (26)

Here $r$ is the distance from the leakage to the surface, and $u'$ is a constant value. From our numerical model (Figure 19(f)) we simulated $U_{max} = 11$ mV at $r = 200$ m. This yields $u' = 2.4$ V m. Using this value, we can estimate the surface differential signal for a reservoir (Reservoir 1) at a depth about 1000 m. In this case, $r$ equals 800 m. This yields a differential SP of 3 mV at the surface. Therefore, even for this reservoir depth the leakage can be detected at the surface. For adjusting the results from the numerical modeling to different reservoirs, this rough estimate can be performed for arbitrary depths.

5.2.2.6 Heterogeneous Reservoir

Can the SP signal be attributed uniquely to leakages? Heterogeneous permeability within Reservoir 1 may cause similar signals as leaky wells. Thus, the surface signal may be misinterpreted. For studying the effect of heterogeneity on the SP signal above the leaky well we assign a ten-fold permeability to all grid cells of Reservoir 1 to the right of the leaky well.

Figure 22 shows the resulting differential surface SP signal to be compared with Figure 19(i). The maximum of the amplitude is similar in both cases, but obviously, the overall shape of both
5 NUMERICAL MODELING

Figure 19: Difference between the signals with and without leakage at the top of the model at different times.

Figure 20: CO₂ injection and leaky well: saturation after 10 days (a) and 100 days (b) simulation time.
5 NUMERICAL MODELING

Figure 21: SP signal of the leaky well scenario as displayed by the ’unsharp mask’ filter (see text for details).

Figure 22: Difference between the signals with and without leakage on the top of the model after 1000 days of injection without leaky well, but with permeability heterogeneity.

SP responses are completely different. Therefore, both cases can be distinguished clearly.

5.2.3 Aquifer Model

Now, we focus on the propagation of a CO\(_2\) within a storage reservoir itself without leakage. To this end, we set up a simple 2D model (Figure 23) of an aquifer for studying whether the CO\(_2\) front can be detected by SP monitoring at the surface or inside monitoring wells before the displacement front reaches these wells. In addition, we study how a heterogeneous permeability distribution affects the SP signal and, hence, whether the SP signal allows to determine the heterogeneity within a reservoir. Table 4 shows all important model parameters.

CO\(_2\) is injected in five grid cells at the lower left corner of the model (see Figure 23). As the right boundary is set to zero saturation and initial pressure and is hence open for fluid flow, CO\(_2\) propagates through the reservoir according to the permeability distribution, displacing water while
Figure 23: Geometry and grid for the aquifer model. The black lines indicate position of the injection well and the monitoring wells at 265.5 m and 512.5 m distance from the injection well.

Table 4: Assumed model parameters as well as fluid and rock properties for the aquifer model. Model Geometry is shown in Figure 23.

<table>
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<th>Parameter</th>
<th>Value</th>
<th>Parameter</th>
<th>Value</th>
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<td>$\rho_n$ (kg m$^{-3}$)</td>
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<td>$\mu_n$ (Pa s)</td>
<td>$3.29 \times 10^{-5}$</td>
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<td>$\rho_f$ (kg m$^{-3}$)</td>
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<td>$\mu_f$ (Pa s)</td>
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<td>$\sigma_f$ (S m$^{-1}$)</td>
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<td>$\sigma_r$ (S m$^{-1}$)</td>
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</tr>
<tr>
<td>$L$ (a aquifer) (A Pa$^{-1}$ m$^{-1}$)</td>
<td>$7.5 \times 10^{-10}$</td>
<td>$L$ (caprock) (A Pa$^{-1}$ m$^{-1}$)</td>
<td>$7.5 \times 10^{-16}$</td>
</tr>
<tr>
<td>$k$ (homogenous aquifer) (m$^2$)</td>
<td>$10^{-12}$</td>
<td>$\log_{10}(k/m^2)$ (heterogeneous aquifer)</td>
<td>-12$\pm$0.5</td>
</tr>
<tr>
<td>$k$ (caprock) (m$^2$)</td>
<td>$10^{-18}$</td>
<td>$n$</td>
<td>1.6 (-)</td>
</tr>
<tr>
<td>$\phi$ (aquifer) (-)</td>
<td>0.2 (-)</td>
<td>$\phi$ (caprock) (-)</td>
<td>0.2 (-)</td>
</tr>
<tr>
<td>$\lambda$ (Brooks-Corey) (-)</td>
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<td>$p_d$ (Pa)</td>
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</tr>
<tr>
<td>$S_{fr}$ (-)</td>
<td>0 (-)</td>
<td>$S_{nr}$ (-)</td>
<td>0 (-)</td>
</tr>
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<td>Simulation time (days)</td>
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<td>Time step (variable)</td>
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<tr>
<td>Injection rate (kg s$^{-1}$)</td>
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<td>Reference potential (V)</td>
<td>U(241,2,1)= 0 V</td>
</tr>
</tbody>
</table>
the propagating.

5.2.4 Surface Signal

Figure 24 shows the propagation of the CO$_2$ injection front for a homogeneous (C) and a heterogeneous (D) permeability distribution after 20 days of injection. Also shown are the corresponding differential SP steps between the simulation days 20 and 19 ($\Delta SP = SP(20) - SP(19)$) recorded at the surface (A and B). The surface SP signal indicates the position of the CO$_2$ front. However, there is only little difference between the SP signals for homogeneous and heterogeneous cases.

Figures 25, 26, 27 and 28 show the evolution of the CO$_2$ plume and differential SP signal with time for 30 days, 40 days, 50 days and 65 days, respectively. In contrast to days 20 and
30, after 40 days of injection, the difference between the two signals is clearly visible (about 12 mV). Therefore, the two cases can be distinguished. Unfortunately, small-scale features of the heterogeneous permeability distribution cannot be resolved as the signal is very smooth at the surface.

The propagation of the front causes an increasing differential SP signal at the surface. The voltage distribution reflects the geometry of the plume. However, after reaching the model boundary, the signal decreases strongly again (see days 50 and 65). This is due to the increasing saturation, resulting in a decreasing coupling coefficient (see equation 19).
Figure 26: CO$_2$ injection front for homogeneous (C) and heterogeneous (D) permeability distribution after 40 days of injection. Also shown are the corresponding surface SP differences between days 40 and 39: $\Delta SP = SP(40) - SP(39)$. 
Figure 27: CO$_2$ injection front for homogeneous (C) and heterogeneous (D) permeability distribution after 50 days of injection. Also shown are the corresponding surface SP differences between days 40 and 39: $\Delta SP = SP(50) - SP(49)$. 

![Diagram showing CO$_2$ injection fronts and SP differences.](image-url)
Figure 28: CO$_2$ injection front for homogeneous (C) and heterogeneous (D) permeability distribution after 65 days of injection. Also shown are the corresponding surface SP differences between days 65 and 64: $\Delta SP = SP(65) - SP(64)$. 
5.2.5 Well Data

As the SP surface signal is not able to reveal a heterogeneous reservoir permeability, now we study whether data from wells within the reservoir is capable to do so. To this end, we use an use just the reservoir section of the model shown in Figure 23 without overburden.

This study is based on an arbitrary heterogeneous permeability distribution (Figure 29) generated with the Sequential Gaussian Simulation algorithm (Deutsch & Journel, 1998). SP and saturation data are recorded within the injection well and at two monitoring wells (Figure 23) at 265.5 m and 512.5 m distance from the injection well. The injection well itself is also a monitoring well.

These data are used for studying whether the heterogeneity of the spatial permeability distribution can be identified and whether SP data are useful for monitoring the CO$_2$ displacement front before it reaches the wells. As stated before, SP data without processing yield little information as the overall SP signal is dominated by the signal originating at the injection point which disguises the signal originating at the displacement front. Therefore, we interpret the differential signal between two days of simulation time.

Figure 30 illustrates saturation and SP difference along the three wells at certain times. Right from the beginning (day 2), the high saturation and pressure change at the injection well (red line) causes a SP differential signal of 0.4 V. This signal is decreasing steadily, again because of the decreasing coupling with increasing saturation (see equation 19). The distribution of saturation
along the well already indicates a heterogeneous permeability. In contrast, the SP signal yields no information on this parameter.

The displacement front reaches the middle monitoring well (blue dashed line) at day 8. However, the SP differential signals indicates the arrival of the front already at day 4 (or, more obvious, day 5). This indicates that SP allows an early detection of the arrival of the CO$_2$ displacement front. Saunders et al. (2008) found that SP signals may be measured at wells 100 m away from the displacement front. This supports our findings. However, the geometry of the front is not yet visible.

During days 9–11, the sign of the differential SP signal changes. This results from the displacement front reaching the well. Injection causes negative SP signals, production positive ones. A front which approaches and moves away causes a similar effect. Now, the first arrival of the major peak of the front is visible in the SP plot separately from the main front. At day 14, secondary peaks become visible in the SP plot. Therefore, the heterogeneous permeability distribution is reflected by SP monitoring data. However, fine structures at a scales < 10 m cannot be identified due to the diffusive character of the electrical signal.

At days 20 and 18, the displacement front and its SP signal reach the last monitoring well, respectively. The differential SP signal appears later because it is much weaker now. This is probably due to the smaller saturation differences between the two phases at the displacement front at larger distance from the injection well and again due to the diffusive character of the SP signal. At day 20, also the SP signal reaches its maximum at the third well.

At later times, e. g. at day 35, the differential SP signal yields no useful information.

In summary, the SP signals yields information on the displacement front before its arrival and on the permeability distribution, but not on small scale variations.

5.2.6 Monte Carlo Inversion

We study whether it is possible to estimate reservoir permeability using the non-wetting phase CO$_2$ as a tracer within a porous medium filled with brine as wetting phase jointly with self-potential
Figure 30: Saturation and corresponding differential $\Delta$SP signal at different times within the injection well and two monitoring wells.
data originating at the displacement front. To this end, we use the heterogeneous aquifer model described above. We use the Metropolis algorithm (Mosegaard & Sambridge, 2002) for estimating permeability.

**5.2.6.1 Metropolis Algorithm**

In this Monte Carlo method, an ensemble of 10,000 equally likely realizations is sampled from a prior probability density function given by a log-normal permeability distribution with $\log_{10}(k/m^2) = -12 \pm 0.5$ generated by Sequential Gaussian Simulation. One of these realizations is assumed to be the synthetic "true" one, called reference model.

Now, simulated saturation and SP data of each realization are compared with perturbed data recorded along wells within the reference model (Figure 31) at $x = 0$ m, $x = 265.5$ m, and $x = 512.5$ m using the root mean square error (RMSE) as objective function. Small RMSE correspond to small misfits.

The RMSE $S$ is calculated from simulated data $d_{i}^{\text{sim}}$ in the $i$th of a total of $n = 123$ cells assigned to the monitoring wells within the particular realization and from the corresponding data from the reference model $d_{i}^{\text{ref}}$:

$$S = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (d_{i}^{\text{sim}} - d_{i}^{\text{ref}})^2}.$$  \hspace{1cm} (27)

The estimation is based on different sources of data and divided into three cases: (i) inversion of saturation data of the non-wetting phase alone; (ii) inversion of electrical SP data alone; (iii) and joint inversion of saturation and SP data.

All data are perturbed by a standard deviation of $\sigma = 0.003$ and 0.01 V for saturation and SP, respectively, to account for measurement errors in a real world’s case.

The posterior probability density function (pdf) is sampled in the following way:

1. Draw an arbitrary sample with RMSE $S_{\text{ref}}$ from the ensemble of realizations.
Figure 31: Permeability $k$ (a), saturation $S$ (b), and absolute SP signal after 67 days of CO$_2$ injection.
2. Accept new sample with RMSE $S_{\text{real}}$ in posterior pdf with probability:

$$P_{\text{acc}} = \begin{cases} 
1 & \text{if } S_{\text{real}} \leq S_{\text{ref}} \\
\exp(-S_{\text{real}} - S_{\text{ref}}) & \text{if } S_{\text{real}} > S_{\text{ref}}
\end{cases}$$  \hspace{1cm} (28)

$\sigma$ is the standard deviation.

3. $S_{\text{real}}$ becomes $S_{\text{ref}}$ when sample is accepted. \(^1\)

4. Proceed with step 1 until all ensemble realizations have been tested.

Figure 32 shows the RMSE for the accepted realizations (hits) for saturation (a) and streaming potential (b) data. Obviously, only realizations with small misfit are accepted, but running into a minimum which does not represent the best fitting solution is avoided.

5.2.6.2 Results

Figure 33 illustrates the estimation results: ensemble mean of accepted realizations (a) as well as the corresponding differences compared to the reference model (b) based on saturation data alone.

\(^{1}\)We call this a hit.
Figure 33: Estimation results (a) as well as the corresponding differences compared to the reference model (b) based on saturation data alone.

Figure 34 and Figure 35 show the results for SP data alone and a joint inversion based on both data sources, respectively.

Joint inversion of saturation and SP data yields similar results. Here, the posterior ensemble contains all accepted realizations from both individual data sources. Both the high permeability region close to the injection area and the low permeability region at the center of the model are identified. However, the dimension of the latter region is clearly underestimated. In addition, all pathways or barriers for fluid flow in the upper and right regions are characterized by large estimation errors. Joint estimation increases the quality of the estimation only little. In summary, only pathways near the injection well can be identified with the Metropolis algorithm. As both types of data used contain more information of the flow field (see Section 5.2.5), we expect an improved estimation quality if using more sophisticated Monte Carlo methods (e.g. Ensemble Kalman Filtering).
Figure 34: Estimation results (a) as well as the corresponding differences compared to the reference model (b) based on SP data alone.
6 Summary and Conclusion

6.1 Single-phase flow

For single-phase fluid flow, an laboratory test facility is now available at GGE allowing measuring the self-potential at different pressure differences and, thus, determining the SP coupling coefficient for porous rock samples.

Single- and multi-phase equations for flow and SP simulations are implemented in our in-house flow and transport simulator SHEMAT-Suite. For the single-phase case, our code is verified again with the analytical solution of a simple well pumping problem.

When assume a coupling coefficient $L = 1.5 \times 10^{-10}$ A Pa$^{-1}$ m$^{-1}$, typical scenarios for CO$_2$ injection (approximated by single-phase simulations) or geothermal applications indicate detectable SP signals in a reservoir at a depth of 300 m below the earth’s surface or a network of monitoring wells. However, storing super-critical CO$_2$ requires elevated pressure and temperature which
occur typically at depths 800 m depth (Büsing et al., 2012). To monitor this depths, observation wells are required.

Large-scale leakages due to an overall leaky overburden are detectable at the surface after several months assuming a reservoir depth of 600 m. Distances of monitoring points between 200 m and 1000 m are sufficient for detecting them in this case.

SP signals can measured even for greater depths when the signal is conducted through a metal well casing. However, these conductive casings disturb significantly the SP distribution, making the identification of moving plumes difficult. For obtaining defined signals, we assumed non-conductive casings in this study.

In an inverse study, we studied the SP signals at three wells of the Enhanced Geothermal System at Soultz-sous-Forêts, France. Unfortunately, synthetic SP data cannot help identifying uniquely the three possible groups of fluid pathways at Soultz classified by Vogt et al. (2012) based in chemical tracer data. However, using the Ensemble Kalman Filter in a synthetic Soultz-like reservoir showed that permeability can be estimated by SP data in a similarway as with tracer data, if a system of deviated micro-drillholes is used for monitoring. Otherwise, high gradients at injection and production points will not present this.

Note that all results need to be interpreted with respect to the assumed coupling coefficient. However, all values can be easily adjusted for different coupling coefficients due to the linear dependency of the SP signal from this coefficient.

### 6.2 Multi-phase flow

Field measurements of the self-potential showed that a CO$_2$ source close to the surface is clearly shows up in the signal.

The saturation-dependence of the coupling coefficient and of the electrical conductivity is implemented in SHEMAT-Suite for numerical multi-phase models. SP signals caused by CO$_2$ displacement fronts are clearly visible in our simulations and are observable 100 m in advance of the front itself. A very important finding is that preferentially differential signals should be
used for identifying the signal originating at the displacement front. This should hold eliminating
the disturbance by the injection pressure. Differences can be calculated between either two times
in one model or two different numerical models for the same time. As an alternative, a dipole
configuration can be used to measure the differential signal (making use of the disturbed symmetry
of the problem). Alternatively, an ‘unsharp mask’ filter can be used when SP images are available.

When studying a leakage scenario we found that identifying leakages based on SP data associated
with injection of CO$_2$ into the ground requires numerical modeling formed for estimating
the SP signal at the surface. These simulation results can then be compared with measured data
for monitoring the overburden for leakages. We found differential SP signals varying from 3 mV
to 12 mV for reservoir depths down to 1000 m. Even for a reservoir at 2600 m, the differential
SP signal was around 1 mV, and, hence, observable by a surface monitoring network. Note, that
real flow rates in reservoirs are expected to be larger than assumed here resulting in even larger
signals. The two alternative cases “leaky well” and “heterogeneous reservoir permeability” can be
distinguished clearly by numerical modeling.

Studying an aquifer injection scenario showed that also the propagation of the plume inside
the reservoir can be observed at the surface based on differential SP monitoring. Heterogeneous
and homogeneous cases can be distinguished, but details of small scale permeability fluctuations
cannot be resolved. In contrast, borehole monitoring of SP allows identifying permeability hetero-
genity. At 100 m ahead of the displacement front, the approaching CO$_2$ plume can be identified,
but details of the spatial heterogeneity cannot be resolved.

A Monte Carlo inversion method (Metropolis algorithm) allowed estimating the basic features
of the permeability field near the injection area. Using SP and saturation data yielded fits of similar
quality.

In the future, we will focus on 3D models of real CO$_2$ sequestration sites such as Ketzin, Ger-
many. In addition, using SP data more effectively we will use gradient-based Bayesian inversion or
sophisticated Monte Carlo inversion methods, such as Ensemble Kalman Filtering, for estimating
permeability or other rock properties such as electrical conductivity or the coupling coefficient.
The Ensemble Kalman Filter provides estimates after each time step in which observations are available.

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**Publications**

During the project, three posters and one talk where presented on scientific conferences, one paper was submitted for publication in the journal Geothermics, one Diploma and one Master thesis was written. One additional paper is in preparation.

**Paper in Peer-Reviewed Journal**


**Posters**

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Talk


Diploma Thesis


Bachelor Thesis

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