Fracture Characterization in Geothermal Reservoirs
Using Time-Lapse Electric Potential Data

Lilja Magnúsdóttir

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FRACTURE CHARACTERIZATION
IN GEOTHERMAL RESERVOIRS
USING TIME-LAPSE ELECTRIC POTENTIAL DATA

A DISSERTATION
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FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

Lilja Magnúsdóttir
August 2013
Abstract

The configuration of fractures in a geothermal reservoir is central to the performance of the system. The interconnected fractures control the heat and mass transport in the reservoir and if the fluid reaches production wells before it is fully heated, unfavorable effects on energy production may result due to decreasing fluid enthalpies. Consequently, inappropriate placing of injection or production wells can lead to premature thermal breakthrough. Thus, fracture characterization in geothermal reservoirs is an important task in order to design the recovery strategy appropriately and increase the overall efficiency of the power production. This is true both in naturally fractured geothermal systems as well as in Enhanced Geothermal Systems (EGS) with man-made fractures produced by hydraulic stimulation.

In this study, the aim was to estimate fracture connectivity in geothermal reservoirs using a conductive fluid injection and an inversion of time-lapse electric potential data. Discrete fracture networks were modeled and a flow simulator was used first to simulate the flow of a conductive tracer through the reservoirs. Then, the simulator was applied to solve the electric fields at each time step by utilizing the analogy between Ohm’s law and Darcy’s law. The electric potential difference between well-pairs drops as a conductive fluid fills fracture paths from the injector towards the producer. Therefore, the time-lapse electric potential data can be representative of the connectivity of the fracture network.

Flow and electric simulations were performed on models of various fracture networks and inverse modeling was used to match reservoir models to other fracture networks in a library of networks by comparing the time-histories of the electric potential. Two fracture characterization indices were investigated for describing the
character of the fractured reservoirs; the fractional connected area and the spatial fractal dimension. In most cases, the electrical potential approach was used successfully to estimate both the fractional connected area of the reservoirs and the spatial fractal dimension. The locations of the linked fracture sets were also predicted correctly. Next, the electric method was compared to using only the simple tracer return curves at the producers in the inverse analysis. The study showed that the fracture characterization indices were estimated somewhat better using the electric approach. The locations of connected areas in the predicted network were also in many cases incorrect when only the tracer return curves were used.

The use of the electric approach to predict thermal return was investigated and compared to using just the simple tracer return curves. The electric approach predicted the thermal return curves relatively accurately. However, in some cases the tracer return gave a better estimation of the thermal behavior. The electric measurements are affected by both the time it takes for the conductive tracer to reach the production well, as well as the overall location of the connected areas. When only the tracer return curves are used in the inverse analysis, only the concentration of tracer at the producer is measured but there is a good correlation between the tracer breakthrough time and the thermal breakthrough times. Thus, the tracer return curves can predict the thermal return accurately but the overall location of fractures might not be predicted correctly.

The electric data and the tracer return data were also used together in an inverse analysis to predict the thermal returns. The results were in some cases somewhat better than using only the tracer return curves or only the electric data. A different injection scheme was also tested for both approaches. The electric data characterized the overall fracture network better than the tracer return curves so when the well pattern was changed from what was used during the tracer and electric measurements, the electric approach predicted the new thermal return better. In addition, the thermal return was predicted considerably better using the electric approach when measurements over a shorter period of time were used in the inverse analysis. In addition to characterizing the fracture distribution better, the electric approach can
give information about the conductive fluid flowing through the fracture network even before it has reached the production wells.
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# Nomenclature

## Variables

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<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
<th>Unit</th>
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<tbody>
<tr>
<td>( a )</td>
<td>Fractal dimension of fracture length distribution</td>
<td>[-]</td>
</tr>
<tr>
<td>( A )</td>
<td>Cross-sectional area</td>
<td>[m²]</td>
</tr>
<tr>
<td>( B )</td>
<td>Chapters 2, 3, and 6: Empirical constant</td>
<td>[-]</td>
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<tr>
<td>( B )</td>
<td>Chapter 5: Proportionality coefficient</td>
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<tr>
<td>( c )</td>
<td>Chapter 2 and Section 3.2: Molar concentration</td>
<td>[M]</td>
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<tr>
<td>( c )</td>
<td>Section 3.1: Conductivity average</td>
<td>[mhos m⁻¹]</td>
</tr>
<tr>
<td>( C )</td>
<td>Fracture density parameter</td>
<td>[-]</td>
</tr>
<tr>
<td>( d )</td>
<td>Empirical constant</td>
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<tr>
<td>( D )</td>
<td>Spatial fractal dimension</td>
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<tr>
<td>( e )</td>
<td>Empirical constant</td>
<td>[-]</td>
</tr>
<tr>
<td>( E )</td>
<td>Electric field</td>
<td>[V/m]</td>
</tr>
<tr>
<td>( f )</td>
<td>Electric potential for a fracture network in the library of networks</td>
<td>[V]</td>
</tr>
<tr>
<td>( g )</td>
<td>Gravitational acceleration</td>
<td>[m/s²]</td>
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<tr>
<td>( G )</td>
<td>Gravitational constant</td>
<td>[m³ kg⁻¹ s⁻²]</td>
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<td>( h )</td>
<td>Chapter 3: Length of block in x-direction</td>
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<tr>
<td>( h )</td>
<td>Chapter 4: Fracture height</td>
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<td>( I )</td>
<td>Electric current</td>
<td>[A]</td>
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<tr>
<td>( J )</td>
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<tr>
<td>( k )</td>
<td>Permeability</td>
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<td>( K )</td>
<td>Geometric factor</td>
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<tr>
<td>( l )</td>
<td>Chapter 3: Length of block in y-direction</td>
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<tr>
<td>( l )</td>
<td>Chapter 5: Length of a square domain</td>
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<td>( L )</td>
<td>Fracture length</td>
<td>[m]</td>
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<tr>
<td>( m )</td>
<td>Chapter 3: Hydraulic mass flow rate</td>
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<tr>
<td>( m )</td>
<td>Chapter 5: Linear fracture density</td>
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<tr>
<td>( M )</td>
<td>Mass</td>
<td>[kg]</td>
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Variables

\( n \) \hspace{1cm} \text{Empirical constant} \hspace{1cm} [-]

\( N(L) \) \hspace{1cm} \text{Number of fractures with lengths larger or equal to } L \hspace{1cm} [-]

\( N(MC) \) \hspace{1cm} \text{Number of Monte Carlo simulations} \hspace{1cm} [-]

\( N(r) \) \hspace{1cm} \text{Number of boxes of size } r \text{ that include the center point of fractures} \hspace{1cm} [-]

\( N_x \) \hspace{1cm} \text{Number of blocks in x-direction} \hspace{1cm} [-]

\( N_y \) \hspace{1cm} \text{Number of blocks in y-direction} \hspace{1cm} [-]

\( p \) \hspace{1cm} \text{Pressure} \hspace{1cm} [\text{Pa}]

\( q(x,y) \) \hspace{1cm} \text{Section 3.1: Current density positioned at point } (x,y) \hspace{1cm} [\text{A/m}^2]

\( q \) \hspace{1cm} \text{Section 3.2: Fluid flow rate} \hspace{1cm} [\text{m/s}]

\( Q \) \hspace{1cm} \text{Section 3.1: Charge density} \hspace{1cm} [\text{C/m}^2]

\( Q \) \hspace{1cm} \text{Section 3.2: Volumetric flow rate} \hspace{1cm} [\text{m}^3/\text{s}]

\( r \) \hspace{1cm} \text{Box length} \hspace{1cm} [\text{m}]

\( r' \) \hspace{1cm} \text{Unit vector} \hspace{1cm} [-]

\( R \) \hspace{1cm} \text{Chapter 2: Radius} \hspace{1cm} [\text{m}]

\( R \) \hspace{1cm} \text{Chapter 3: Resistance} \hspace{1cm} [\text{ohm}]

\( R \) \hspace{1cm} \text{Chapter 5: Region} \hspace{1cm} [-]

\( R \) \hspace{1cm} \text{Chapter 8: Coefficient of determination} \hspace{1cm} [-]

\( SS \) \hspace{1cm} \text{Sum of squares} \hspace{1cm} [-]

\( T \) \hspace{1cm} \text{Temperature} \hspace{1cm} [\degree \text{C}]

\( v \) \hspace{1cm} \text{Multiplier used to shift eigenvalues} \hspace{1cm} [-]

\( V \) \hspace{1cm} \text{Electric potential} \hspace{1cm} [\text{V}]

\( V \) \hspace{1cm} \text{Chapter 4: Average velocity} \hspace{1cm} [\text{m/s}]

\( W \) \hspace{1cm} \text{Weighting factor} \hspace{1cm} [-]

\( Z \) \hspace{1cm} \text{Least squares criterion} \hspace{1cm} [\text{V}]

\( \Gamma \) \hspace{1cm} \text{Transmissibility} \hspace{1cm} [\text{m}^3]

\( \epsilon \) \hspace{1cm} \text{Error} \hspace{1cm} [\text{V}]

\( \theta \) \hspace{1cm} \text{Fracture orientation} \hspace{1cm} [\degree]

\( \Lambda \) \hspace{1cm} \text{Molar concentration coefficient} \hspace{1cm} [-]

\( \mu \) \hspace{1cm} \text{Fluid viscosity} \hspace{1cm} [\text{Pa s}]

\( \rho \) \hspace{1cm} \text{Section 3.1: Resistivity} \hspace{1cm} [\text{ohm m}]

\( \rho \) \hspace{1cm} \text{Section 3.2: Fluid density} \hspace{1cm} [\text{kg/m}^3]

\( \sigma \) \hspace{1cm} \text{Conductivity} \hspace{1cm} [\text{mhos m}^{-1}]

\( \tau \) \hspace{1cm} \text{Connectivity index} \hspace{1cm} [-]

\( v \) \hspace{1cm} \text{Connectivity indicator} \hspace{1cm} [-]

\( \phi \) \hspace{1cm} \text{Rock porosity} \hspace{1cm} [-]
**Subscripts**

- \( e \)  Earth
- \( err \)  Error
- \( scale \)  Used for scaling
- \( tot \)  Total
- \( v \)  Support
- \( i, j, k, l, x, y \)  Various indices
- \( p \)  Compression
- \( s \)  Shear
- \( w \)  Water

**Abbreviations**

- DFN: Discrete Fracture Network
- EGS: Enhanced Geothermal System
- ERT: Electrical Resistivity Tomography
- FCA: Fractional Connected Area
- GPR: Ground-Penetrating Radar
- GPRS: General Purpose Research Simulator
- GPS: Global Positioning System
- LHS: Left Hand Side
- MC: Monte Carlo
- McMC: Markov-chain-Monte-Carlo
- PDF: Partial Differential Equation
- RHS: Right Hand Side
- SP: Self-Potential
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Chapter 1

Introduction

Geothermal energy is heat extracted from the ground, coming from earth’s interior heat source and circulation. The energy is abundant and renewable, and was in earlier years used mainly for bathing, cooking and relaxation. Geothermal energy was first used for power generation at Larderello, Italy in 1904. Since that time, geothermal power production has begun in many countries worldwide. Wells are usually drilled 2-3 km deep into the earth and hot water or steam is piped up to a power plant to drive steam turbines. The steam spins turbine blades in the turbine generators to produce electricity. Lower temperature resources often make use of binary power plants in which geothermal heat is transferred to a secondary working fluid in heat exchangers, then the working fluid drives the turbine.

A geothermal system requires heat, permeability and water. The system can be recharged by an input of magmatic fluid but cold waste water is usually injected into the reservoir to maintain fluid and pressure in the system. The injected water flows through fractures and pore-spaces and extracts heat from the hot rock. In systems where permeability is not sufficient, hydraulic stimulation can be used to increase the permeability of the rock and these systems are called Enhanced Geothermal Systems (EGS). In fractured reservoirs, it is important to place the injection wells appropriately so the injected water heats up sufficiently before reaching the production wells. An optimal injection strategy includes maximizing the sweep efficiency of the injected water and avoiding premature thermal
interference at production wells. Characterizing fractures in the reservoirs is a difficult task but the knowledge of the fluid-flow patterns is extremely valuable for the development of an optimal injection strategy.

In this study, fractured geothermal reservoirs were studied. The possibility of using a time-lapse inversion of electrical resistivity data with conductive fluid injection to estimate fracture connectivity was investigated. The study focused on the use of fracture characterization to increase the efficiency of the system and prevent premature thermal breakthrough.

1.1 Background

Connectivity of fractures in both natural and Enhanced Geothermal Systems (EGS) is a key factor in interpreting fracture flow, to ensure adequate supply of geothermal fluids and efficient thermal operation of the wells. The interconnected conductive fractures control mass and heat transport in the system and inappropriate placement of injection or production wells can lead to premature thermal breakthrough of colder reinjected fluid. Reinjection of spent geothermal fluid has become a standard practice in reservoir management for waste disposal and to improve the total energy recovery. The replacement of reservoir fluid helps maintaining reservoir pressure and can increase energy extraction efficiency. However, the reinjected water can flow prematurely through highly conductive fractures back into production wells, thereby reducing the discharge enthalpy and the useful energy output. Such premature thermal breakthroughs have occurred in numerous geothermal reservoirs, as described by Horne [47], and observed worldwide including at The Geysers [7], Miravalle [80], and Cerro Prieto [75].

Chemical tracers have been used to investigate connectivity between wells in order to prevent premature thermal breakthrough [30, 31]. By injecting a slug of tracer, Shook [90] showed how tracer histories could be transformed into predicted temperature histories in heterogeneous porous media but the method’s accuracy degraded in the presence of a strong permeability correlation. Wu et al. [106] predicted enthalpy production in fractured geothermal reservoirs using a single fracture model
which was also expanded to a two-phase flow scenario in a network of multiple fractures. Analysis of tracer data yielded fracture properties that were used to simulate the enthalpy production but the fracture network contained only parallel vertical fractures. Other methods include using assumptions of specific flow channels connecting injection and production wells with tracer tests to predict premature thermal breakthrough [41]. Such methods can be powerful during early stages of production but more complex models are needed where the flow mechanism is highly complicated. Thus, tracer testing is a potentially powerful technique but accurate interpretation of tracer results in highly fractured reservoirs can be difficult.

Application of geophysical methods (discussed in Chapter 2) has been useful for obtaining physical parameters of the earth system including temperature, elastic properties, density, magnetic susceptibility, and electric conductivity. Conventional wellbore-based techniques for characterizing flow in the subsurface include core sample analysis and well-logging. These techniques can give information about the rock type, porosity, and temperature but do not provide information about key controls on overall subsurface flow behavior in fractured reservoirs. Seismic surveys have been used to identify boundaries between flow units in aquifer systems [19, 81] but depth constraints were necessary to reduce uncertainty. Thus, seismic surveys can be useful to study shallow aquifers but it is challenging to detect small-scaled fractures at greater depths. Jeannin et al. [52] detected fractures in rocks using Ground-Penetrating Radar (GPR) but the antennae reached a maximum penetration of 20 m. Garg et al. [35] described how self-potential, magnetotelluric and direct current surveys were all used to explore the Beowawe geothermal field in the Basin and Range Province of the western USA. These exploration techniques are commonly used to find hidden geothermal resources that lack hydrothermal surface features, identify promising drilling targets and to help designing recovery strategies appropriately [42, 45, 95]. They can provide valuable information regarding properties in the subsurface but the relationship between hydraulic and geophysical properties might not be known. A variety of other approaches has been attempted to combine multiple geophysical methods to better quantify hydrological properties in the subsurface. Garambosis et al. [33] used Ground-Penetrating Radar
(GPR), seismic, and electric methods to characterize physical properties and the influence of water in the subsurface. However, measurements were only performed on near-surface formations. Geophysical surveys performed at the surface do not offer a high level of resolution when exploring deeper portions of the reservoirs.

Other approaches include locating measurement tools inside wells to increase the depth resolution, and using time-dependent geophysical data that indirectly can measure time-varying hydraulic parameters [24, 48]. Electrical resistivity has been shown to be sensitive to changes in fluid conductivity and water content in reservoirs [8, 108], and the concentration of a conductive tracer can be mapped from field measurements of resistance using cross-well Electrical Resistivity Tomography (ERT) [93]. A number of studies have demonstrated the potential of ERT for monitoring tracer migration in soil [9, 61, 78, 94], and in shallow aquifers [18, 77, 91, 92]. In these studies, usually many electrodes were used to obtain the resistivity distribution for the whole field under study at each time step and then this resistivity distribution was compared to the distribution without any tracer. That way, resistivity changes in each block could be observed and in some cases effective hydraulic conductivities were estimated. Using this approach for a whole reservoir would require a massive parameter space and likely not be solvable, except at very low resolution.

Day-Lewis et al. [23] demonstrated the benefits of time-lapse inversion of geophysical data over the previously mentioned conventional ‘snapshot’ approach. Lambot et al. [63] showed how Ground-Penetrating Radar (GPR) was used with hydrodynamic inverse modeling to identify effective hydraulic properties of sand in laboratory conditions. Irving and Singha [50] have also demonstrated an attempt to use Bayesian Markov-chain-Monte-Carlo (MCMC) methodology to jointly invert dynamic cross-well and surface resistivity data with tracer concentration data to estimate hydraulic conductivities in heterogeneous geological environments. They concluded that using resistivity data instead of tracer data alone was worth the most where flow was controlled largely by highly connected flow paths. These methods provided a potential framework for estimating hydraulic properties but none of them was used to characterize fracture networks representing common geothermal reservoirs, which is the focus of the work presented in this dissertation.
1.2 Objective

The overall objective of this study was to characterize fractures in geothermal reservoirs. Various geophysical exploration techniques were explored and the method chosen for this study consisted of using electric potential difference calculations between geothermal wells with a conductive fluid injection. The goal was to first study the changes in electric potential difference, corresponding to apparent resistivity, as a conductive tracer was injected into the reservoir. Then the goal was to study the possibility of using that response, i.e. potential difference vs. time, in an inverse modeling process to obtain a fracture network characterization index. An important part of the project was to find a suitable characterization index to quantify fracture properties. Thus, instead of determining the location of each fracture in the system, a characterization index was to be estimated to better understand the character of the fracture network and thereby help preventing premature thermal breakthrough.

1.3 Outline

This dissertation is outlined as follows.

Chapter 1 states the problem, lists some of previous efforts to solve it and briefly describes the objective of this study.

Common geophysical exploration techniques are summarized in Chapter 2. The chapter describes the electrical resistivity method chosen for this study and provides a comparison to other geophysical exploration techniques.

Modeling the electrical resistivity method required simulating electric fields. A description of how electric fields of fracture networks were simulated in this study is given in Chapter 3.

Chapter 4 provides a description of how electric fields of discrete fracture networks change as a conductive fluid is injected into the reservoirs. The electric potential difference between wells drops as more paths are filled with conductive fluid due to
the lower resistivity of the fluid. Thus, the time-history of the electric potential
difference depends on the flow paths and could be used for fracture characterization.

Finding a suitable fracture characterization index to describe the fracture
networks is discussed in Chapter 5. Spatial fractal dimension was considered as well
as Fractional Connected Area (FCA).

In Chapter 6 the process of using an inversion of time-lapse electrical resistivity
data to estimate spatial fractal dimension and FCA is outlined.

Results are given in Chapter 7. The electric potential approach was compared
to using only the tracer return curves to estimate the spatial fractal dimension and
FCA.

The possibilities of using the electric potential approach to estimate thermal
breakthrough are discussed in Chapter 8. The approach was compared to using
only the tracer return curves and to using a joint inversion of electric and tracer data.
The electric approach was also compared to using only the tracer return curves for a
different well layout than used for the tracer and electric measurements. In addition,
the possibility of using the approach for measurements performed over a short period
of time was investigated.

Chapter 9 concludes this dissertation by summarizing the main conclusions and
listing recommendations for future work.
Chapter 2

Overview of Geophysical Exploration Methods

The extraction of steam or hot water from the earth is a very crucial and expensive process in geothermal power plants. Determining the optimum location of wells is critical and it is important to develop methods to increase the reliability of the wells drilled. Subsurface fluid-thermal interaction can seldom be exactly quantified and analyzed, but the first step in the development of a geothermal resource for electric power or hot water production involves geothermal exploration. The knowledge obtained through exploration is the basis for locating sites which can be used for energy generation and for evaluating suitability of such sites for geothermal development. Geothermal systems are often accompanied by outflows of mass and heat to the earth’s surface but many hidden systems have been discovered accidentally as a result of drilling for water, oil and gas, or mineral resources [34]. However, random searches for geothermal systems would not be favorable and geothermal exploration can be necessary to identify good drilling targets.

Geophysical methods have also been used to detect flow paths in geothermal reservoirs, which is the main focus of this study. Finding the location of fracture zones is important for modeling fluid flow and understanding the behavior of the rock-fluid system. That way, an optimal injection strategy can be designed to prevent premature thermal breakthrough. Many physical parameters of deep
geological formations can be obtained from the surface via geophysical methods (e.g., temperature, elastic properties, density, magnetic susceptibility, and electric conductivity) to gain information about the fluid flow in the reservoir. Geophysical exploration methods can be classified as either active or passive methods. Passive methods incorporate measurements of naturally occurring fields or properties of the earth, for example gravity surveys. On the other hand, active geophysical surveys involve injecting a signal into the earth and measuring the earth's response to the signal. Those signals could for example be an electrical current or an active radiometric source. Examples of active methods are seismic reflection and electrical resistivity methods.

In this chapter, an overview of common geophysical exploration methods is given with the intent to explain why the electrical resistivity method was chosen for this study. In the first section, the direct current resistivity method is described and factors affecting resistivity of water-saturated rocks are listed. Then, the following geophysical methods are summarized briefly; gravity surveys, seismic surveys, electromagnetic surveys, magnetotelluric surveys, self-potential surveys, well logging, and tracer testing.

2.1 Direct Current Resistivity Surveys

In electrical resistivity surveys the resistivity of the subsurface is calculated from electrical measurements. First, a direct current is sent into the ground through current electrodes and the voltage differences between voltage electrodes are recorded. Then, the input current and measured voltage difference give information about the subsurface resistivity. The current and potential electrodes are generally arranged in a linear array, as shown in Figure 2.1, where an ammeter measures the total current going into the ground through electrodes at points A and B and a voltmeter measures the potential difference between electrodes at points M and N.

Resistivity measurements have been commonly used in various industries such as medicine, archeology, and reservoir engineering. In the medical industry resistivity measurements have been used to image the internal conductivity of the human body,
for example to monitor epilepsy, strokes, and lung functions as discussed by Holder [46]. Resistivity measurements have also been used to image archaeological features and patterns [74], as well as to map aquifers. For example, Arnarson [3] describes how different surface resistivity measurements have been efficiently used in Iceland to locate high temperature fields in geothermal reservoirs. Pritchett [83] concluded based on a theoretical study that hidden geothermal resources can be discovered by electrical resistivity surveys because geothermal reservoirs are usually characterized by substantially reduced electrical resistivity relative to their surroundings. Electrical current moving through the reservoir passes mainly through fluid-filled fractures and pore spaces because the rock itself is normally a good insulator. Stacey et al. [97] investigated the feasibility of using resistivity to measure core saturation. A direct current pulse was applied through electrodes attached in rings around a sandstone core and it resulted in data that could be used to infer the resistivity distribution and thereby the saturation distribution in the core. It was also concluded by Wang and
Horne [102] that resistivity data has a high resolution power in depth direction and is capable of sensing areal heterogeneity.

Electrical resistivity surveying is usually done at the earth’s surface. However, it can also be done by placing one current and one voltage electrode inside a geothermal well and the other electrodes on the surface or inside another well. A general configuration of a cross-well resistivity survey is shown in Figure 2.2. This method can provide detailed information about the resistivity distribution between the wells as demonstrated by Daniels and Dyck [22]. They concluded that well-to-surface systems can provide detailed information concerning areal positions, while well-to-well measurements yield the best depth resolution.

![Figure 2.2: General configuration of two current electrodes (A and B) and two voltage electrodes (M and N) in a cross-well resistivity survey.](image)

The electrical resistivity of a water-saturated rock depends on several factors including temperature, water saturation, salinity of the saturating water and the rock’s alteration mineralogy. Resistivity ranges for a few materials are listed in Table
2.1. The resistivity typically covers a wide range because the geological formations vary in porosity, moisture content, temperature and mineral composition.

<table>
<thead>
<tr>
<th>Materials</th>
<th>Resistivity [ohm-m]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Saline water (20%)</td>
<td>0.05</td>
</tr>
<tr>
<td>Saline water (3%)</td>
<td>0.15</td>
</tr>
<tr>
<td>Clay</td>
<td>5 – 150</td>
</tr>
<tr>
<td>Gravel</td>
<td>480 – 900</td>
</tr>
<tr>
<td>Limestone</td>
<td>350 – 6,000</td>
</tr>
<tr>
<td>Sandstone (consolidated)</td>
<td>1,000 – 4,000</td>
</tr>
<tr>
<td>Igneous rock</td>
<td>100 – 1,000,000</td>
</tr>
</tbody>
</table>

The relationship between resistivity and temperature of water is shown in Figure 2.3. Electrical conductivity of water is mainly due to movement of ions, and Quist and Marshall [85] showed that at lower temperatures the viscosity of water decreased as the temperature increased which led to an increase in the mobility of ions and hence a lower resistivity. The minimum in isobaric specific resistivity results near 300-400 °C, and above that temperature, the number of dissociated ions in the solution decreases as the dielectric permittivity of water decreases, which increases the fluid resistivity.

The resistivity increases as well with decreasing porosity of water-saturated rocks. Archie [2] proposed the following relation between the bulk resistivity, $\rho$, of water-saturated rocks to the resistivity of water, $\rho_w$, and the porosity of the rock, $\phi$,

$$\rho = d \phi^{-e} \rho_w$$

where $d$ and $e$ are empirical constants. Archie [2] concluded that for typical sandstones of oil reservoirs the coefficient $d$ is approximately 1 and $e$ is approximately 2 but Keller
and Frischknecht [56] showed that this power law is valid with varying coefficients based on the rock type.

Salinity of the geothermal brine in the rock has also a large effect on the resistivity. Ucok et al. [100] have established experimentally the resistivity of saline fluids over the temperature range 20-350°C and their results for resistivity of a NaCl solution calculated using a three-dimensional regression formula is shown in Figure 2.4. Ucok et al. [100] calculated that the dependence of resistivity is best represented by the formula:

$$\rho_w = b_0 + b_1 T^{-1} + b_2 T + b_3 T^2 + b_4 T^3$$  \hfill (2.2)

where $T$ is temperature and $b$ are coefficients found empirically. The best fit for the concentration dependence was found to be:
Figure 2.4: Resistivity of a NaCl solution as a function of temperature and concentration [100].
\[ \rho_w = \frac{10}{(\Lambda c)} \]  \tag{2.3}\\

where
\[
\Lambda = B_0 - B_1 c^{1/2} + B_2 c \ln(c) + \text{higher order terms} \]  \tag{2.4}\\

Coefficients \( B \) depend on the solution chemistry and \( c \) is the molar concentration.

Another factor affecting the resistivity is the mineral alteration of the rock, which causes interface conductivity as the minerals line the walls of the fractures. The resistivity changes due to those minerals depend on the temperature and the chemical composition of the rock as well as the saturation fluid. These different factors affecting the resistivity of water-saturated rock can make it difficult to distinguish between water-filled fractures and rock that has low resistivity due to some other factors. However, in order to increase the contrast in resistivity between rock and fractures, a saline tracer can be injected into the reservoir and the movement of the tracer can be visualized using Electrical Resistivity Tomography (ERT). A number of studies have demonstrated the potential of using ERT to monitor tracer migration [9, 18, 61, 77, 78, 91, 92, 94]. The electrical potential of the field is measured while the conductive fluid flows through the flow system. Then, the electrical potential measurements at each time step can be inverted to find the resistivity distribution of the reservoir. The changes in resistivity as conductive flows from an injector towards a producer can also be used to determine hydraulic conductivities of grid blocks representing the reservoir.

In these methods, each tomogram is typically inverted independently and the data are collected quickly enough to monitor the flow behavior of the conductive fluid, as
illustrated in Figure 2.5. Day-Lewis et al. [23] demonstrated the benefits of using

time-lapse inversion of geophysical data instead of independent inversion. Then, the
time-history of the geophysical data is collected and used in one inversion to determine
hydraulic properties of the reservoir, as illustrated in Figure 2.6. Irving and Singha
[50] demonstrated how time-lapse inversion of tracer and resistivity data could be
used to estimate hydraulic conductivities in a heterogeneous geological environment.
Time-lapse inversion of resistivity with electrodes located inside wells was chosen
for this study as it provides a potential framework for detecting and characterizing
fractures located deep in geothermal reservoirs.
Figure 2.5: Independent inversion of each tomogram during an injection of a conductive fluid.
Figure 2.6: Time-lapse inversion of conductivity data measured during an injection of a conductive fluid.
2.2 Comparison to Other Geophysical Methods

In addition to the resistivity method, other geophysical methods have been used successfully for geothermal exploration. The methods described in this section are gravity surveys, seismic surveys, electromagnetic surveys, magnetotelluric surveys, self-potential surveys, well logging, and tracer testing. Advantages and disadvantages of each method are listed to explain why the resistivity method was found to be advantageous as compared to other methods for fracture characterization in deep reservoirs.

2.2.1 Seismic Surveys

Seismic surveys record acoustic echoes from the rock layers by transmitting sound into the ground and recording the energy that reflects back at different times and locations on the surface. Later arrival times of transmitted waves are associated with changes in velocity within the medium along the travel path, meaning that the seismic energy passed through slow regions and early arrivals relate to fast regions. The variation in travel times can then be associated with changes in material properties and thereby used to form a geologic map of the subsurface [17]. These methods that use cross-correlation of noise records between geophones to extract information on the distribution of subsurface structures have become more popular in recent years [39]. However, seismic surveys do not always provide the best results, because data can be smeared by effects from mountain slopes and fluvial patterns. Also, the processing of the signals is compute-intensive and the equipment is expensive. The field is still very much in development [101]. In comparison to the resistivity method, an advantage of using electric resistivity is that porosity, pore fluid conductivity, saturation and
temperature all influence resistivity so it has a more direct relationship to fractures in the reservoir than the seismic parameters do.

### 2.2.2 Gravity Surveys

The gravity method is a nondestructive geophysical technique that involves measurements of the gravitational field at a series of different locations. The variations in gravity are associated with differences in the distribution of densities and hence rock types. The method is concerned with acceleration at the earth’s surface to determine subsurface variations in mass distributions. That involves solving the following equation for gravitational acceleration, $g$, due to some mass distribution,

$$g = GM_e \frac{r'}{R_e^2}$$

(2.5)

where $M_e$ is the mass of the earth, $G$ is the universal gravitational constant, $R_e$ is the radius of the earth, and $r'$ is a unit vector extending downward towards the center of the earth. The force is therefore proportional to the mass of the object and decreases with distance [67].

A historical outline of the early development of the gravity method of exploration is given by Eckhardt [27]. The fundamentals of interpretation are the same today as they were 25 years ago, but Global Positioning Systems (GPS) and powerful computers have revolutionized the speed and utility of the method [70]. The advantage of the gravity method is that no energy needs to be put into the ground in order to acquire data since the method is passive, and it is relatively cheap and noninvasive. The disadvantage of the method is that earth’s gravitational field measured at the surface
is not only affected by different densities, so data must be corrected to account for distortions such as topographic changes, the shape of the earth, rotation, and tides. Another major disadvantage of underground gravity surveys is poor lateral resolution and many gravity anomalies cannot be resolved due to insufficient geologic information. Thus, it would be very challenging to use a gravity survey to characterize fracture patterns.

2.2.3 Electromagnetic Surveys

In electromagnetic surveys the principle of induction is used to measure the electrical conductivity of different rocks and materials of the subsurface in order to characterize their structural and spatial locations. Usually, the method consists of two large coils, a sending coil and a receiving coil. A primary alternating electric current of known frequency and magnitude is passed through the sending coil creating a magnetic field. The eddy currents generated in the ground induce a secondary current in underground conductors which results in an alternating secondary magnetic field, sensed by the receiving coil. The conductivity of the field is proportional to the ratio of the magnitudes of the primary and secondary currents and the transmitted field travels deeper if the coils are spread further apart. In a similar approach, a Ground-Penetrating Radar (GPR) is used where pulses of high-frequency electromagnetic waves are emitted into the subsurface through a transmitting antenna. The reflected electromagnetic energy is received at one or more locations along the surface and the reflected energy versus time is converted to depth using knowledge of the propagation velocity within the soil. These electromagnetic surveys can typically only be used up to a depth of 1 km when performed on the surface [3]. However, placing the
transmitter and receiver inside wells gives a better depth resolution. A cross-well electromagnetic tomography method was used successfully in a 600 m deep field in Texas to obtain conductivity images of an injected slug of salt water [104]. Similar to the resistivity method, electromagnetic surveys have a good potential for geothermal exploration and fracture characterization. The main difference from the resistivity method is that the anomalies in resistivity methods result from resistivity contrasts while with electromagnetic methods anomalies are due more to absolute resistivity [58].

2.2.4 Magnetotelluric Surveys

The magnetotelluric method is a combination of telluric and magnetic methods that involves comparison of the horizontal components of the magnetic and electric fields associated with the flow of telluric currents. The method can map resistivity variations from near surface to depths of several kilometers and has for example been used to provide reliable information about the location and characterization of the most promising geothermal systems in El Salvador [88]. The magnetotelluric surveys are cheap and can be used to recognize fluid-filled volumes but the technique is based on a weak natural signal so it cannot be used everywhere. The geometric resolution is poor and it can be difficult to distinguish alteration clays from actual fluid circulation.

2.2.5 Self-Potential Surveys

The Self-Potential (SP) method is a passive electrical method. Potential differences that occur naturally in the earth without inducing current into the subsurface, are
measured along two electrodes that are placed into the soil and connected to a voltmeter. The potential is caused by fluid flow through the porous medium and ion exchange between the fluid and soil particles. Information about the location, flow magnitude and the depths and geometries of subsurface flow paths can be provided by the measurement of relatively small voltage anomalies.

Self-Potential (SP) anomalies have been used in a considerable number of geothermal areas to describe geothermal activity. For example, Hase et al. [43] discuss how SP observation was used to infer hydrothermal systems beneath Usu volcano in Japan. They compiled a map from SP surveys that revealed positive anomalies that corresponded to fumarolic areas likely to be affected by hydrothermal systems. Ishido et al. [51] describe how numerical simulation calculations were used to characterize fractured reservoirs using a combination of pressure and self-potential transient data. When self-potential surveys are used alone, noise and data reproducibility problems are often encountered, which are more severe in large-scale geothermal surveys [21]. Electrical resistivity methods were found likely to give stronger anomalies for characterizing fracture zones.

2.2.6 Well Logging

Well logging involves making a detailed record of the geologic formations penetrated by a borehole by lowering instruments into the hole for measurements. This method can give good information about the temperature, pressure, rock porosity and rock type, which is important for example to differentiate between sandstones which are good sources of fluids and shale which can surround other rock layers and trap fluids. Well logging only provides information at discrete locations and although it can give
information about the fracture density at these locations, it cannot identify fractures located between the wells.

2.2.7 Tracer Tests

Tracer tests are a mixture of qualitative and numerical analysis methods used to determine flow paths in the reservoir. The tracer is injected at injection wells and the time history of the tracer collected at production wells is studied. A considerable number of papers have been presented describing successful well tracer tests that indicate which wells are connected and infer the properties of the fracture network between them. For example, Gaoxuan et al. [32] discuss how tracer recovery of injected solute were used to infer flow channels between two wells. Kocabas [60] also showed how tracer injection-backflow tests could be used to characterize the region of potential injectors. Tracer testing is a powerful technique to estimate the likelihood of premature thermal breakthrough but accurate interpretation of tracer results in highly fractured reservoirs may be difficult. Juliusson and Horne [53] concluded based on numerical simulations that tracer returns can give information about which wells are connected through a fracture network, but that they can not be used to make conclusive remarks about which wells are not connected.

2.3 Summary

This chapter provided a description of the electrical resistivity method and a brief summary of other geophysical exploration methods commonly used to explore geothermal reservoirs. The pros and cons of each methods were discussed with the
intent to explain why electrical resistivity method was chosen for this study. Currently, none of the geophysical exploration methods are capable of providing an accurate high resolution model of geothermal reservoirs at the required scale, depth and cost for running the power plants in an optimal way. However, the electric resistivity method has a good potential for detecting water-filled fractures in the reservoir due to the large contrast in resistivity between rock and water. Additionally, a saline tracer can be injected into the reservoir to enhance the contrast in resistivity between rock and fractures zones, and electrodes placed inside geothermal wells can give a better depth resolution.
Chapter 3

Electric Field Simulations

The electrical resistivity method described in Chapter 2 requires simulating electric fields based on resistivity distributions. This chapter describes the approaches that were used in this study to calculate the electric fields in geothermal reservoirs. First, a resistivity model was developed where Poisson equation was solved on a structured grid. Then, the possibility of using flow simulators TOUGH2 [54] and General Purpose Research Simulator (GPRS) [16] to solve electric fields was investigated. That way, the same grid on which fractures in the network are solved discretely, could be used for simulating the flow of a conductive tracer as well as to simulate the electric flow. For verification, the resistivity model was compared to the Partial Differential Equation (PDE) ToolboxTM in Matlab [49]. Electric calculations using TOUGH2 were compared to the resistivity model and an analytical solution. GPRS was verified via a comparison to an analytical solution and was also compared to TOUGH2.
3.1 Resistivity Model

One of the main problems in resistivity modeling is to solve the Poisson equation that describes the potential field and to complete the inversion iteration efficiently. That governing equation can be derived from basic electrical relationships as described by Dey and Morrison [26]. Ohm’s Law defines the relationship between current density, \( J \), conductivity of the medium, \( \sigma \), and the electric field, \( E \), as:

\[
J = \sigma E \quad (3.1)
\]

The stationary electric fields are conservative, so the electric field at a point is equal to the negative gradient of the electric potential, i.e.:

\[
E = -\nabla V \quad (3.2)
\]

where \( V \) is the scalar field representing the electric potential at the given point. Hence,

\[
J = -\sigma \nabla V \quad (3.3)
\]

Current density is the movement of charge density, so according to the continuity equation, the divergence of the current density is equal to the rate of change of charge density,

\[
\nabla J = \frac{\partial Q(x,y)}{\partial t} = q(x,y) \quad (3.4)
\]
where \( q(x,y) \) is the current density \([\text{A/m}^2]\) positioned at point \((x,y)\). Combining Equations (3.3) and (3.4) gives the following Poisson equation which describes the potential distribution due to a point source of excitation,

\[
\nabla [\sigma \nabla V] = -q(x, y)
\]

The conductivity \( \sigma \) is in mhos m\(^{-1}\) and the electric potential \( V \) is in volts. This partial differential equation can then be solved numerically for the resistivity problem.

### 3.1.1 Finite Difference Equations in Two Dimensions

Finite difference method is used to approximate the solution to Equation (3.5) in two dimensions using a point-discretization of the subsurface [68]. The computational domain is discretized into \( Nx \times Ny \) blocks and the distance between two adjacent points on each block is \( h \) in x-direction and \( l \) in y-direction, as shown in Figure 3.1.
Taylor series expansion is used to approximate the derivatives of Equation (3.5) about a point \((j,k)\) on the two-dimensional grid,

\[
\frac{\partial}{\partial x} \left( \sigma \frac{\partial V}{\partial x} \right) \bigg|_{j,k} \approx \frac{-[\sigma(j + \frac{1}{2}, k)\sigma(j - \frac{1}{2}, k)]V(j, k)}{h^2}
\]

(3.6)

\[
\frac{\partial}{\partial y} \left( \sigma \frac{\partial V}{\partial y} \right) \bigg|_{j,k} \approx \frac{-[\sigma(j + \frac{1}{2}, k)\sigma(j - \frac{1}{2}, k)]V(j, k)}{l^2}
\]

(3.7)

The point \((j,k)\) represents the shaded area in Figure 3.1 (area = \(hl\)) so the current density due to an electrode at that point is given by,

\[
q(j, k) = \frac{I}{hl}
\]

(3.8)

where \(I\) [A] is the current injected at point \((j,k)\). Combining Equations (3.5)-(3.8) and solving for the electric potential \(V\) at point \((j,k)\) gives,

\[
V(j, k) = \frac{[Ihl + V(j + 1, k)c_1l^2 + V(j - 1, k)c_2l^2 + V(j, k + 1)c_3h^2 + V(j, k - 1)c_4h^2]}{[c_1 + c_2]l^2 + [c_3 + c_4]h^2}
\]

(3.9)

The parameters \(c_i\) represent the conductivity average between two adjacent blocks, i.e.

\[
c_1 = \frac{2}{\rho(j, k)\rho(j + 1, k)}
\]

(3.10)
\[ c_2 = \frac{2}{\rho(j, k)\rho(j - 1, k)} \]  
\[
\tag{3.11}
\]
\[ c_3 = \frac{2}{\rho(j, k)\rho(j, k + 1)} \]  
\[
\tag{3.12}
\]
\[ c_4 = \frac{2}{\rho(j, k)\rho(j, k - 1)} \]  
\[
\tag{3.13}
\]

where \( \rho(j, k) \) is the resistivity [ohm-m] of the node at grid coordinates \( j,k \).

### 3.1.2 Iteration Method

In order to solve Equation (3.9) numerically and obtain the results for electrical potential \( V \) at each point on the grid, an iteration method called Successive Over-Relaxation was used [96]. At first, a guess is made for \( V(j, k) \) across the whole grid, for example \( V(j, k) = 0 \) for all \( j,k \). That guess is then used to calculate the right-hand side of Equation (3.9) (RHS) for each point and the new set of values for \( V(j, k) \) is calculated using the following iteration scheme,

\[ V_{n+1} = vRHS + (1 - v)V_n \]  
\[
\tag{3.14}
\]

The multiplier \( v \) is used to shift the eigenvalues so the iteration converges better than simple relaxation. The number \( v \) is between 1 and 2, and when the computing region is rectangular the following equation can be used to obtain a reasonable value for \( v \),

\[ v = \frac{2}{1 + \sqrt{1 - S^2}} \]  
\[
\tag{3.15}
\]
In this study the iteration was run until this error criterion was reached,

\[ \epsilon = \left| \frac{LHS - RHS}{V_{scale}} \right| < 10^{-10} \]

where LHS is the left-hand side of Equation (3.9) and \( V_{scale} \) is a scale voltage which is on the order of the biggest voltage in the problem. This error criterion ensures that the Poisson equation is satisfied [96].

Natural Neumann boundary conditions were used on the outer boundaries. The derivative of \( V \) at the boundary was set equal to zero by adding a row of elements around the field under study and defining \( V \) at these elements equal to \( V \) at the boundary of the field.

### 3.1.3 Resistivity Model Compared to PDE Toolbox in Matlab

The resistivity model was tested for a \( 100 \times 100 \) m\(^2 \) field with homogeneous resistivity set as 1 ohm-m. The field was discretized into \( 50 \times 50 \) elements so the element size was \( 2 \times 2 \) m\(^2 \). The grid is shown in Figure 3.2a where the gray elements represent the elements around the field that were modeled to implement natural Neumann boundary conditions at the field boundaries. A current was set equal to 1 A at the four corner points of the element shown in red, and as -1 A at the four corner points of the element shown in green. Then, the potential field was solved, results are shown in Figure 3.3a. For comparison, a similar homogeneous field was solved using the Partial Differential Equation (PDE) Toolbox in Matlab [49]. The discretized field is shown
in Figure 3.2b. In the PDE toolbox, the electric currents were defined as boundary conditions, set as 1 A around the square shown in red and as -1 A around the square shown in green. The results for the electric field calculated using the PDE toolbox are shown in Figure 3.3b. The field calculated using the resistivity model is very similar to the one calculated using the PDE toolbox in Matlab. The small difference is likely due to different ways of defining the current and due to different discretization methods. The current was defined at nodes in the resistivity model but can only be defined as boundary conditions in the PDE toolbox, and a fine triangular mesh was used in the PDE toolbox while regular squared elements were used in the resistivity model. However, despite these different configurations, both models showed similar behavior of the electric field.

Although the PDE toolbox in Matlab contains tools to preprocess, solve and postprocess partial differential equations in two dimensions using finite elements, it could not be used to calculate electric fields for the fractured reservoirs in this study. Unlike the resistivity model, it does not solve a potential field for inhomogeneous resistivity which is essential for modeling resistivity contrasts between rock and fractures. The drawback of using the resistivity model is that only structured grids can be modeled so the fractures need to be either modeled as coarse-scaled grid blocks or the whole field under study needs to be discretized into small grid blocks, which would not be feasible when modeling large geothermal fields with small-scaled fractures. Thus, in order to be able to define the matrix grid blocks larger than the fracture elements without developing a complicated resistivity model, the possibility of using a flow simulator to solve the electric field was investigated.
Figure 3.2: Discretization of the field for a) the resistivity model and b) the PDE Toolbox in Matlab.
Figure 3.3: Potential distribution [V] for a homogeneous resistivity field calculated using a) the resistivity model and b) the PDE Toolbox in Matlab.
3.2 Electric Field solved using a Flow Simulator

The analogy between Ohm’s law and Darcy’s law has been well established [12, 69]. The potential distribution in a steady-state flow through a porous medium is exactly the same as the electrical potential distribution in an electrically conducting medium. Darcy’s law defines the relationship between the fluid flow rate \( q \) [m/s], permeability \( k \) [m\(^2\)], viscosity of the fluid \( \mu \) [Pa s], and pressure \( p \) [Pa],

\[
q = -\frac{k}{\mu} \nabla p
\]  

(3.18)

Similarly, Ohm’s law defines the relationship between electric potential \( V \) [V], current density \( J \) [A/m\(^2\)], and conductivity \( \sigma \) [mhos m\(^{-1}\)],

\[
J = -\sigma \nabla V
\]  

(3.19)

Table 3.1 outlines the analogy between the flow of an electric current and the flow of water.

<table>
<thead>
<tr>
<th>Property</th>
<th>Darcy’s Law</th>
<th>Ohm’s Law</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flux of:</td>
<td>Water ( q )</td>
<td>Charge ( J )</td>
</tr>
<tr>
<td>Potential:</td>
<td>Pressure ( p )</td>
<td>Voltage ( V )</td>
</tr>
<tr>
<td>Medium property:</td>
<td>Hydraulic conductivity ( \frac{k}{\mu} )</td>
<td>Electrical conductivity ( \sigma )</td>
</tr>
</tbody>
</table>

Table 3.1: Analogy between the flow of an electric current and the flow of water.

A number of studies have utilized this analogy between Ohm’s law and Darcy’s law to simulate fluid flow in porous medium [14, 105]. In this study, a fluid flow simulator was used to solve the flow of an electric current. That way, a Discrete
Fracture Network (DFN) approach introduced by Karimi-Fard et al. [55] could be used to solve for the flow of a conductive tracer as well as the electric flow in a network of fractures. This method is based on an unstructured control volume finite-difference formulation where the cell connections are defined using a connectivity list and fractures are treated discretely. Every element (both triangles and fracture segments) are given a transmissibility value related to the flow between two adjoining elements,

\[ Q_{ij} = \Gamma_{ij} (p_j - p_i) \]  

(3.20)

where \( Q \) is the volumetric flow rate between gridblocks \( i \) and \( j \), and \( \Gamma \) is the transmissibility. Thus, more realistic fracture patterns can be modeled than when using the resistivity model described in Section 3.1, where fractures would be defined by high permeability values in relatively course-scale grid blocks.

The pressure results from a flow simulator correspond to the electric voltage, as shown in Table 3.1. Thus, a voltage drop or a potential difference between two points is equal to a pressure difference between these points. An illustration of the analogy between the flow of water and an electric circuit is given in Figure 3.4. The water is assumed to flow horizontally when electric flow is simulated using a flow simulator so that the force of gravity can be ignored. The electric current \( I \) [A] is analogous to the hydraulic volumetric flow rate, \( Q \) [m\(^3\)/s], but the hydraulic mass flow rate, \( \dot{m} \) [kg/s], is entered in the input file for the flow simulator. The relationship between the hydraulic volumetric flow rate and the hydraulic mass flow rate is,

\[ \dot{m} = \rho Q = \rho I \]  

(3.21)
Figure 3.4: Analogy between water and a direct current circuit. The figure was edited from a figure published by Nave [72].

where \( \rho \) is the density of the fluid \([\text{kg/m}^3]\). Thus, when solving for electric flow using a flow simulator, the mass flow rate in the input file is defined as the input current multiplied by the fluid density. The hydraulic conductivity corresponds to the electrical conductivity, so the permeability, \( k \ [\text{m}^2] \), for each element in the input file for the flow simulator is defined as,

\[
k = \sigma \mu \tag{3.22}
\]

where \( \sigma \ [\text{mhos m}^{-1}] \) is the electric conductivity of the element and \( \mu \ [\text{Pa s}] \) is the viscosity of water. The density and viscosity of water changes with temperature and pressure, as shown in Figure 3.5 for the viscosity of water at 150°C. Thus, it is important to use the appropriate density in Equation 3.21 and appropriate viscosity in Equation 3.22, that correspond to the pressure and temperature conditions in the simulation.
Additionally, some of the parameters in the simulation need to be scaled because the pressure conditions in flow simulations are normally of a higher order of magnitude than the voltage in electric simulations. In the simulations in this study, the injection/production rate was scaled if it was too low to produce sufficient significant digits for the electric results. Then, the pressure results were divided by the same factor that the injection/production rate was multiplied by to obtain the right voltage results. In some cases the permeability was also scaled as demonstrated in Section 3.2.2. The initial pressure in the flow simulator for the simulations in this study was defined as $10^6$ Pa. When looking at the resistivity in a geothermal field the electric potential difference between wells was studied so the initial pressure cancels out when the pressure difference is calculated. However, for
the simple block matrices in the next section where exact electric voltage values of each block were studied, the initial pressure (10^6 Pa) was subtracted from the pressure results to obtain the electric potential results for zero initial voltage. All simulations were carried out until steady-state conditions were reached.

3.2.1 Electric Field solved using TOUGH2

TOUGH2 [54] is a flow simulator that simulates fluid flow under pressure, viscous, and gravity forces according to Darcy’s law (Equation 3.18). The possibility of using TOUGH2 to calculate an electric field was first investigated using the EOS9 module and then using the EOS1 module in TOUGH2. The liquid viscosity, density and compressibility can be defined constant when using the EOS9 module, making the imitation of electric flow possible. However, the EOS9 module did not work with the discrete fracture network approach used in this study so the possibility of using the EOS1 module was also investigated. The drawback of using the EOS1 module is that the dependency of viscosity, density and compressibility on pressure and temperature is automatically taken into account while in the electric simulation the conductivity should not depend on the electric voltage.

Electric Field Simulations Compared to the Resistivity Model

The EOS9 module in TOUGH2 considers flow of a single aqueous phase consisting of a single water component [54]. The conditions are assumed to be isothermal so only a single water mass balance equation is solved for each grid block and the thermal properties of water can be overwritten. Therefore, liquid viscosity, density and compressibility can be defined constant and reference pressure and temperature
can be overwritten. The electric field was calculated for a simple $3 \times 3$ block matrix with dimensions $10 \times 10$ m$^2$, shown in Figure 3.6. The EOS9 module in TOUGH2 was used with constant fluid viscosity defined as $2 \times 10^{-4}$ Pa s. This constant viscosity defined in the input file was then used in Equation 3.22 to calculate the permeability corresponding to the resistivity of the field. The resistivity was set as 0.1 ohm-m and the electric current was set as 3 A in the block in the upper left corner and as -3 A in the block in the lower right corner. The electric parameters and corresponding input in TOUGH2 are summarized in Table 3.2.

The constant density in the TOUGH2 input file was defined as 1000 kg/m$^3$ so the electric current was multiplied by 1000 kg/m$^3$ to get the fluid injection rate as shown in Equation 3.21. Then, that fluid injection rate was multiplied by $1 \times 10^5$ to produce sufficient pressure changes in the simulation and thereby more accuracy in the electric results. The initial pressure was set as $10^6$ Pa, so to calculate the electric results the pressure results were reduced by subtracting $10^6$ Pa to impose zero initial voltage. Then, the results were divided by $1 \times 10^5$ to account for the scaling of the injection and production rates. The results were verified by a comparison to the resistivity model described in Section 3.1. TOUGH2 and the resistivity model gave the same solution for electric voltage, shown in Table 3.3. The rows of the tables represent the rows of blocks shown in Figure 3.6.
Table 3.2: Flow parameters and corresponding electric parameters for the matrix in Figure 3.6.

<table>
<thead>
<tr>
<th></th>
<th>SI-units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Permeability (resistivity):</td>
<td>$2 \times 10^{-3} \text{ m}^2$ (0.1 ohm-m)</td>
</tr>
<tr>
<td>Flow rate (current) at injector:</td>
<td>$3 \times 10^8 \text{ kg/s}$ (3 A)</td>
</tr>
<tr>
<td>Flow rate (current) at producer:</td>
<td>$3 \times 10^8 \text{ kg/s}$ (-3 A)</td>
</tr>
<tr>
<td>Initial pressure (voltage):</td>
<td>$10^6 \text{ Pa}$ (0 V)</td>
</tr>
<tr>
<td>Fluid density:</td>
<td>$1000 \text{ kg/m}^3$</td>
</tr>
<tr>
<td>Fluid viscosity:</td>
<td>$2 \times 10^{-4} \text{ Pa s}$</td>
</tr>
<tr>
<td>Simulation time:</td>
<td>10 days</td>
</tr>
<tr>
<td>Upper limit for time steps:</td>
<td>100 s</td>
</tr>
</tbody>
</table>

Figure 3.6: Homogeneous electric model with the current set as 3 A in the upper left corner and as -3 A in the lower right corner.

Table 3.3: Electric potential for the matrix in Figure 3.6 calculated using the resistivity model and the EOS9 module in TOUGH2.

<table>
<thead>
<tr>
<th></th>
<th>0.225 V</th>
<th>0.075 V</th>
<th>0 V</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.075 V</td>
<td>0 V</td>
<td>-0.075 V</td>
<td>-0.225 V</td>
</tr>
</tbody>
</table>

An inhomogeneous case was studied as well, shown in Figure 3.7. The resistivity of the blue blocks was defined as 0.005 ohm-m and the resistivity of the gray block was defined as 0.0025 ohm-m. The electric current was set as 3 A in the block in the upper
Figure 3.7: Inhomogeneous electric model with the current set as 3 A in the upper left corner and as -3 A in the lower right corner.

left corner and as -3 A in the block in the lower right corner, and the initial electric potential was set as zero. The same procedure as before was used to define the input parameters in the TOUGH2 input file for the EOS9 module. The constant viscosity and density were the same as for the previous example, as well as the injection rates. Thus, the only difference between this case and the previous case was that for this case the permeability of the blue blocks was set as 0.04 m$^2$ and the permeability of the gray block was set as 0.08 m$^2$. For this inhomogeneous case, the results from TOUGH2 were also the same as the results for the resistivity model, shown in Table 3.4. Thus, these results demonstrated that the EOS9 module in TOUGH2 could be used to calculate the electric fields for a homogeneous case and an inhomogeneous case by defining the water density and viscosity in the flow simulation constant.
Table 3.4: Electric potential for the matrix in Figure 3.7 calculated using the resistivity model and EOS9 module in TOUGH2.

<table>
<thead>
<tr>
<th></th>
<th>0.0107 V</th>
<th>0.0032 V</th>
<th>0 V</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0032 V</td>
<td>0 V</td>
<td>-0.0032 V</td>
<td></td>
</tr>
<tr>
<td>0 V</td>
<td>-0.0032 V</td>
<td>-0.0107 V</td>
<td></td>
</tr>
</tbody>
</table>

Fracture Network Analyzed as an Electric Circuit

The previous section demonstrated that a flow simulator could be used to solve the flow of an electric current. However, it was not possible to use the EOS9 module in TOUGH2 with the Discrete Fracture Network (DFN) formulation used in this study. Therefore, the possibility of solving for electric flow using the EOS1 module [54] that works with DFNs was investigated. The EOS1 module describes water in its liquid, vapor, and two-phase states. EOS1 can be used to solve for two waters with identical physical properties, and can therefore be used to solve for tracer flow. The only drawback is that when using the EOS1 module in TOUGH2 to solve for electric flow, the viscosity, compressibility and density dependency on pressure and temperature is automatically taken into account. In the electric simulation, the conductivity of the reservoir (corresponding to permeability divided by viscosity) does not depend on the electric voltage (corresponding to pressure). Thus, when solving for electric flow using the EOS1 module it is important that the viscosity used in Equation 3.22 is close to the true viscosity for the pressure and temperature conditions in the simulation. Similarly, the electric current has to be multiplied by the appropriate fluid density. It is also necessary to specify the parameters \((NK, NEQ, NPH, NB) = (1, 1, 2, 6)\) in data block MULTI. With this option, isothermal conditions are assumed and only liquid is present in the reservoir. The method of calculating electric flow using the EOS1 module in TOUGH2 was tested for the fracture network in Figure
3.8, referred to as Fracture Network Ia, and the results compared to an analytical solution of an electric circuit corresponding to the fracture network. In a geothermal reservoir, water-filled fractures act in many ways like an electric circuit because the fractures form low-resistivity paths from the injector to the producer. The electric current travels mainly through these paths due to the high resistivity of the reservoir. The reservoir properties for Fracture Network Ia are summarized in Table 3.5 and Figure 3.9 demonstrates the electric circuit corresponding to Fracture Network Ia. All the fractures were assumed to be filled with water with NaCl concentration equal to 0.5 wt%. The tracer concentration was first changed into molar concentration and then the three-dimensional regression analysis by Ucok et al. [100] was used to calculate the resistivity of the conductive fluid.
\\( \rho_w = b_0 + b_1 T^{-1} + b_2 T + b_3 T^2 + b_4 T^3 \) \hspace{1cm} (3.23)
\\( \rho_w = 10/(\Lambda c) \) \hspace{1cm} (3.24)
\\( \Lambda = B_0 - B_1 c^{1/2} + B_2 c \ln(c) + \text{higher order terms} \) \hspace{1cm} (3.25)

where \( T \) is temperature, \( c \) is the molar concentration, and \( B \) are coefficients found empirically.

\[
B = \begin{bmatrix}
3.470 & -6.650 & 2.633 \\
-59.23 & 198.1 & 64.8 \\
0.4551 & -0.2058 & 0.005799 \\
-0.346 \times 10^{-5} & 7.368 \times 10^{-5} & 6.741 \times 10^{-5} \\
-1.766 \times 10^{-6} & 8.787 \times 10^{-7} & -2.136 \times 10^{-7}
\end{bmatrix}
\] \hspace{1cm} (3.26)

Then, the resistivity of the water-saturated rock was defined using Archie’s law [2] (Equation 2.1) with \( d \) equal to 1 and \( e \) equal to 2.

The resistance, \( R \) [ohm], of the resistors in the electric circuit was calculated using the following relationship,
\\( R = \frac{\rho L}{A} \) \hspace{1cm} (3.27)

where \( L \) [m] is the length and \( A \) [m\(^2\)] is the cross-sectional area of the corresponding water-filled fracture. Table 3.6 shows the resistivity and dimensions of the fractures in Fracture Network Ia as well as the calculated resistance of the resistors in the electric circuit in Figure 3.9.

The \( Y - \Delta \) transformation theory published by Kennelly [57] was used to simplify the resistors into a single equivalent resistor. The electric current at one end of the
resistor was set as -1 A and as 1 A at the other end to simulate the current flow through the fractures from the injector to the producer. The voltage drop in the electric circuit was calculated using Ohm’s law (Equation 3.1) and compared to the voltage drop for the fracture network computed using the EOS1 module in TOUGH2. The computational grid for TOUGH2 was formed using the triangular mesh generator Triangle, developed by Shewchuk [89]. The viscosity at the initial temperature and pressure conditions in the reservoir is equal to \(8.8899 \times 10^{-4}\) Pa s, which is the viscosity used in Equation 3.22 to calculate the permeability corresponding to the resistivity. Other properties for the electric simulation are given in Table 3.5. The injection
Table 3.5: Reservoir properties for Fracture Network Ia.

<table>
<thead>
<tr>
<th>Reservoir</th>
<th></th>
<th>SI-units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dimension:</td>
<td>30 $\times$ 30 $\times$ 1 m$^3$</td>
<td></td>
</tr>
<tr>
<td>Fracture width:</td>
<td>$2 \times 10^{-3}$ m</td>
<td></td>
</tr>
<tr>
<td>Fracture porosity:</td>
<td>0.9</td>
<td></td>
</tr>
<tr>
<td>Matrix porosity:</td>
<td>0.1</td>
<td></td>
</tr>
<tr>
<td>Initial temperature:</td>
<td>25$^\circ$C</td>
<td></td>
</tr>
<tr>
<td>Tracer concentration:</td>
<td>0.5 wt%</td>
<td></td>
</tr>
</tbody>
</table>

| Grid |  |
| Max. fracture element size: | 0.5 m | |
| Minimum angle: | 30$^\circ$ | |

| Electric Simulation |  |
| Flow rate (current) at injector: | 1000 kg/s (1 A) | |
| Flow rate (current) at producer: | 1000 kg/s (-1 A) | |
| Initial pressure (voltage): | $10^6$ Pa (0 V) | |
| Fluid density: | 1000 kg/m$^3$ | |
| Fluid viscosity: | $8.889 \times 10^{-4}$ Pa s | |
| Simulation time: | 10 days | |
| Upper limit for time steps: | 100 s | |

The rate was set as 1000 kg/s and the production rate as -1000 kg/s to account for water density which is close to 1000 kg/m$^3$ at these conditions. The simulation time was set as 10 days but the simulation ended once ten consecutive time steps had convergence on iteration one, that is when steady-state conditions had been reached. The voltage drop calculated for the electric circuit was equivalent to the voltage drop between the injector and the producer computed using TOUGH2, results are shown in Table 3.7. Thus, the EOS1 module in TOUGH2 was used successfully to calculate the electric potential for Fracture Network Ia with sufficient accuracy.
Table 3.6: Fracture properties for Fracture Network Ia and the resistance of the corresponding resistors.

<table>
<thead>
<tr>
<th>Resistor</th>
<th>Resistance [ohm]</th>
<th>Resistivity [ohm-m]</th>
<th>Length [m]</th>
<th>Area [m²]</th>
</tr>
</thead>
<tbody>
<tr>
<td>R1</td>
<td>1.02 × 10⁴</td>
<td>1.1086</td>
<td>18.3504</td>
<td>2 × 10⁻³</td>
</tr>
<tr>
<td>R2</td>
<td>8.61 × 10²</td>
<td>1.1086</td>
<td>1.5527</td>
<td>2 × 10⁻³</td>
</tr>
<tr>
<td>R3</td>
<td>2.61 × 10²</td>
<td>1.1086</td>
<td>0.4717</td>
<td>2 × 10⁻³</td>
</tr>
<tr>
<td>R4</td>
<td>1.10 × 10³</td>
<td>1.1086</td>
<td>1.9930</td>
<td>2 × 10⁻³</td>
</tr>
<tr>
<td>R5</td>
<td>4.06 × 10²</td>
<td>1.1086</td>
<td>0.7328</td>
<td>2 × 10⁻³</td>
</tr>
<tr>
<td>R6</td>
<td>5.99 × 10³</td>
<td>1.1086</td>
<td>10.8083</td>
<td>2 × 10⁻³</td>
</tr>
<tr>
<td>R7</td>
<td>1.08 × 10³</td>
<td>1.1086</td>
<td>1.9557</td>
<td>2 × 10⁻³</td>
</tr>
<tr>
<td>R8</td>
<td>9.34 × 10³</td>
<td>1.1086</td>
<td>16.8501</td>
<td>2 × 10⁻³</td>
</tr>
<tr>
<td>R9</td>
<td>7.19 × 10³</td>
<td>1.1086</td>
<td>12.9682</td>
<td>2 × 10⁻³</td>
</tr>
<tr>
<td>R10</td>
<td>7.23 × 10³</td>
<td>1.1086</td>
<td>13.0385</td>
<td>2 × 10⁻³</td>
</tr>
<tr>
<td>R11</td>
<td>4.26 × 10³</td>
<td>1.1086</td>
<td>7.6888</td>
<td>2 × 10⁻³</td>
</tr>
<tr>
<td>R12</td>
<td>3.88 × 10³</td>
<td>1.1086</td>
<td>6.9923</td>
<td>2 × 10⁻³</td>
</tr>
<tr>
<td>R13</td>
<td>3.23 × 10³</td>
<td>1.1086</td>
<td>5.8305</td>
<td>2 × 10⁻³</td>
</tr>
<tr>
<td>R14</td>
<td>7.32 × 10²</td>
<td>1.1086</td>
<td>1.3202</td>
<td>2 × 10⁻³</td>
</tr>
<tr>
<td>R15</td>
<td>5.57 × 10³</td>
<td>1.1086</td>
<td>10.0439</td>
<td>2 × 10⁻³</td>
</tr>
<tr>
<td>R16</td>
<td>2.61 × 10³</td>
<td>1.1086</td>
<td>4.7168</td>
<td>2 × 10⁻³</td>
</tr>
<tr>
<td>R17</td>
<td>2.45 × 10³</td>
<td>1.1086</td>
<td>4.4149</td>
<td>2 × 10⁻³</td>
</tr>
<tr>
<td>R18</td>
<td>1.05 × 10⁴</td>
<td>1.1086</td>
<td>18.9228</td>
<td>2 × 10⁻³</td>
</tr>
<tr>
<td>R19</td>
<td>8.88 × 10³</td>
<td>1.1086</td>
<td>16.0268</td>
<td>2 × 10⁻³</td>
</tr>
<tr>
<td>R20</td>
<td>9.11 × 10³</td>
<td>1.1086</td>
<td>16.4397</td>
<td>2 × 10⁻³</td>
</tr>
<tr>
<td>R21</td>
<td>2.40 × 10³</td>
<td>1.1086</td>
<td>4.3327</td>
<td>2 × 10⁻³</td>
</tr>
</tbody>
</table>

Table 3.7: Electric potential difference for Fracture Network Ia calculated using TOUGH2 and an electric circuit.

<table>
<thead>
<tr>
<th>System</th>
<th>Voltage drop [V]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electric circuit</td>
<td>1.1964 × 10⁴</td>
</tr>
<tr>
<td>Fracture network</td>
<td>1.1980 × 10⁴</td>
</tr>
</tbody>
</table>

3.2.2 Electric Field solved using GPRS

The possibility of using General Purpose Research Simulator (GPRS) developed at Stanford University [16] to calculate electric fields was studied because numerical errors sometimes came up when using flow simulator TOUGH2 to simulate flow in
discrete fracture networks. The error message was 'run-time error M6201: MATH - sqrt: DOMAIN error', which indicates that the program might for instance be taking a square root of a negative value. Thus, it was of interest to study the possibility of using GPRS with discrete fracture networks. In addition, water viscosity and density can be defined constant when using GPRS, which was not possible with discrete fracture networks in TOUGH2. GPRS does not have a geothermal model so a black-oil model was used with the properties of oil defined the same as for water. The units are in oil-field units so the parameters were converted from SI units to oil-field units using the conversion factors shown in Table 3.8. In addition, the bottom-hole pressure was defined at the producer when using GPRS instead of defining a constant flow rate. The voltage drops between an injector and a producer were studied for a field with one fracture and results compared to the corresponding electric circuit. Then, Fracture Network Ia was studied and results compared to the voltage drop for the corresponding electric circuit and to results previously calculated using TOUGH2.

### Table 3.8: Conversion from SI units to oil-field units.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Conversion</th>
<th>Oil-field units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dimension: [m]</td>
<td>× 3.2808</td>
<td>ft</td>
</tr>
<tr>
<td>Permeability: [m²]</td>
<td>× 1.0133 × 10¹⁵</td>
<td>md</td>
</tr>
<tr>
<td>Flow rate: [kg/s]</td>
<td>× 5.4343 × 10²</td>
<td>STB/day</td>
</tr>
<tr>
<td>Pressure: [Pa]</td>
<td>× 1.1450 × 10⁻⁴</td>
<td>psi</td>
</tr>
<tr>
<td>Productivity index: [m³]</td>
<td>× 3.3243 × 10¹⁵</td>
<td>md ft</td>
</tr>
<tr>
<td>Density: [kg/m³]</td>
<td>× 0.0624</td>
<td>lb/ft³</td>
</tr>
<tr>
<td>Temperature: ([°C] + 273.15)×9/5</td>
<td></td>
<td>R</td>
</tr>
</tbody>
</table>
Electric Field solved for a Reservoir with One Fracture

A simple two-dimensional field with one fracture was studied, shown in Figure 3.10. The reservoir properties were the same as for the previous example, shown in Table 3.5, except that in this case the network had dimensions $1000 \times 1000 \times 1$ m$^3$. The resistivity was also calculated the same way as for the previous example, i.e. using Archie’s law [2] (Equation 2.1) and the regression formula studied by Ucok et al. [100] (Equations 3.23-3.25). The fracture was assumed to be filled with water with NaCl concentration equal to $5.4 \times 10^{-2}$ wt\% which resulted in fracture resistivity equal to 6.9 ohm-m. The resistivity of the matrix was set very high as before so that the current would flow only through the fracture.

The constant viscosity of the fluid was defined as $2 \times 10^{-4}$ Pa s and the constant density was defined as 1000 kg/m$^3$ in the input file for GPRS. Then, Equation 3.21 was used to calculated the flow rate at the wells and Equation 3.22 was used to calculate the permeability input for the flow simulator. The properties for the electric simulation are summarized in Table 3.9. The current was set as 1 A at the injector and as -1 A at the producer but it was necessary to scale the corresponding injection rate for the flow simulator. The flow rate was divided by $10^3$ and the pressure results were multiplied by $10^3$ to obtain the electric results. The voltage drop over an electric circuit with one resistor corresponding to the fracture in the field was also calculated. The resistance of the resistor was computed using Equation 3.27. The solution for the electric potential difference between the injector and the producer was equivalent to the voltage drop over the electric circuit. The results are shown in Table 3.10.
Figure 3.10: A field with one fracture.
### Table 3.9: Reservoir and simulation properties for the fracture network in Figure 3.10.

<table>
<thead>
<tr>
<th></th>
<th>SI-units</th>
<th>oil-field units</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Reservoir</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dimension</td>
<td>1000×1000×1 m³</td>
<td>3281×3281×3.281 ft³</td>
</tr>
<tr>
<td>Fracture width</td>
<td>2×10⁻³ m</td>
<td>6.56×10⁻³ ft</td>
</tr>
<tr>
<td>Fracture porosity</td>
<td>0.9</td>
<td>0.9</td>
</tr>
<tr>
<td>Matrix porosity</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>Initial temperature</td>
<td>25°C</td>
<td>536.67 R</td>
</tr>
<tr>
<td>Tracer concentration</td>
<td>5.4×10⁻² wt%</td>
<td>5.4×10⁻² wt%</td>
</tr>
<tr>
<td><strong>Grid</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Max. fracture element size</td>
<td>0.5 m</td>
<td>1.64 ft</td>
</tr>
<tr>
<td>Minimum angle</td>
<td>25°</td>
<td>25°</td>
</tr>
<tr>
<td><strong>Electric Simulation</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Flow rate (current) at injector</td>
<td>1 kg/s (1 A)</td>
<td>543.43 STB/d (1 A)</td>
</tr>
<tr>
<td>BHP (current) at producer</td>
<td>10⁶ Pa (-1 A)</td>
<td>145.0377 psi (-1 A)</td>
</tr>
<tr>
<td>Product. index at producer</td>
<td>4×10⁻¹² m³</td>
<td>13123.36 md-ft</td>
</tr>
<tr>
<td>Initial pressure (voltage)</td>
<td>10⁶ Pa (0 V)</td>
<td>145.0377 psi (0 V)</td>
</tr>
<tr>
<td>Fluid density</td>
<td>1000 kg/m³</td>
<td>62.4 lbm/ft³</td>
</tr>
<tr>
<td>Fluid viscosity</td>
<td>8.889×10⁻⁴ Pa s</td>
<td>0.8889 cp</td>
</tr>
<tr>
<td>Simulation time</td>
<td>86400 s</td>
<td>1 day</td>
</tr>
<tr>
<td>Upper limit for time steps</td>
<td>8640 s</td>
<td>0.1 days</td>
</tr>
<tr>
<td>Lower limit for time steps</td>
<td>86.4 s</td>
<td>1×10⁻³ days</td>
</tr>
</tbody>
</table>

### Table 3.10: Electric potential difference for the network in Figure 3.10 using GPRS and an electric circuit.

<table>
<thead>
<tr>
<th></th>
<th>GPRS</th>
<th>Electric Circuit</th>
</tr>
</thead>
<tbody>
<tr>
<td>9.287×10⁶</td>
<td>9.284×10⁶</td>
<td></td>
</tr>
</tbody>
</table>
Electric Field solved for Fracture Network Ia

Fracture Network Ia was also studied using GPRS, the discretized network is shown in Figure 3.11. In GPRS all fractures not contributing to the electric circuit were excluded. The electric current only travels through the fractures included in Figure 3.11 so for the electric simulation the reservoir is essentially the same as Fracture Network Ia (Figure 3.8), studied previously using TOUGH2. The permeability and input current were calculated the same way as before, with viscosity and density defined constant. The parameters had to be scaled differently to obtain sufficient significant digits in the electric results using GPRS. The scaling of the parameters is listed in Table 3.11 and the properties for the electric simulation are shown in Table 3.12. The results were compared to the previously calculated analytical solution for Fracture Network Ia, and the solution using the EOS1 module in TOUGH2. The results listed in Table 3.13 demonstrate that the results using GPRS are equivalent to the analytical solution and in this case estimate the electric potential difference even more precisely than the EOS1 module in TOUGH2.

Table 3.11: Scaling of electric parameters for the input in GPRS for Fracture Network Ia.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Multiplied by:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flow rate at injector</td>
<td>$10^{-3}$</td>
</tr>
<tr>
<td>Permeability</td>
<td>$10^{-4}$</td>
</tr>
<tr>
<td>Pressure results</td>
<td>10</td>
</tr>
</tbody>
</table>
Figure 3.11: Fracture Network Ia excluding fractures not contributing to the electric circuit in Figure 3.9.
Table 3.12: Reservoir and simulation properties for Fracture Network Ia when using GPRS.

<table>
<thead>
<tr>
<th></th>
<th>SI-units</th>
<th>oil-field units</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Reservoir</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dimension:</td>
<td>$30 \times 30 \times 1 \text{ m}^3$</td>
<td>$98.42 \times 98.42 \times 3.281 \text{ ft}^3$</td>
</tr>
<tr>
<td>Fracture width:</td>
<td>$2 \times 10^{-3} \text{ m}$</td>
<td>$6.56 \times 10^{-3} \text{ ft}$</td>
</tr>
<tr>
<td>Fracture porosity:</td>
<td>0.9</td>
<td>0.9</td>
</tr>
<tr>
<td>Matrix porosity:</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>Initial temperature:</td>
<td>$25^\circ\text{C}$</td>
<td>536.67 \text{ R}</td>
</tr>
<tr>
<td>Tracer concentration:</td>
<td>0.5 wt%</td>
<td>0.5 wt%</td>
</tr>
<tr>
<td><strong>Grid</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Max. fracture element size:</td>
<td>3 m</td>
<td>9.84 ft</td>
</tr>
<tr>
<td>Minimum angle:</td>
<td>25\°</td>
<td>25\°</td>
</tr>
<tr>
<td><strong>Electric Simulation</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Flow rate (current) at injector:</td>
<td>1 kg/s (1 A)</td>
<td>543.43 STB/d (1 A)</td>
</tr>
<tr>
<td>BHP (current) at producer:</td>
<td>$10^6 \text{ Pa}$ (1 A)</td>
<td>145.0377 psi (1 A)</td>
</tr>
<tr>
<td>Product. index at producer:</td>
<td>$4 \times 10^{-12} \text{ m}^3$</td>
<td>13123.36 md-ft</td>
</tr>
<tr>
<td>Initial pressure (voltage):</td>
<td>$10^6 \text{ Pa}$ (0 V)</td>
<td>145.0377 psi (0 V)</td>
</tr>
<tr>
<td>Fluid density:</td>
<td>1000 kg/m$^3$</td>
<td>62.4 lbm/ft$^3$</td>
</tr>
<tr>
<td>Fluid viscosity:</td>
<td>$8.889 \times 10^{-4} \text{ Pa s}$</td>
<td>0.8889 cp</td>
</tr>
<tr>
<td>Simulation time:</td>
<td>86400 s</td>
<td>1 day</td>
</tr>
<tr>
<td>Upper limit for time steps:</td>
<td>8640 s</td>
<td>0.1 days</td>
</tr>
<tr>
<td>Lower limit for time steps:</td>
<td>86.4 s</td>
<td>$1 \times 10^{-3}$ days</td>
</tr>
</tbody>
</table>

Table 3.13: Comparison of electric potential difference for Fracture Network Ia using GPRS, an electric circuit, and TOUGH2.

<table>
<thead>
<tr>
<th></th>
<th>GPRS</th>
<th>Electric Circuit</th>
<th>TOUGH2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$1.1969 \times 10^4 \text{ V}$</td>
<td>$1.1964 \times 10^4 \text{ V}$</td>
<td>$1.1980 \times 10^4 \text{ V}$</td>
</tr>
</tbody>
</table>
3.3 Summary

This chapter demonstrated approaches to calculate electric fields that were verified via a comparison to other methods. The chapter was divided into two sections, one described a structured-grid resistivity model and the other section described how flow simulators could be used to calculated electric fields. The resistivity model was used mainly to verify the electric field calculations when using a flow simulator. TOUGH2 and GPRS were both used successfully to calculate electric fields of discrete fracture networks. Flow simulator TOUGH2 was used for the electric field simulations shown in Chapter 4 but GPRS was used for the simulations in Chapters 5-8 because GPRS was found to work better and be more robust when solving for flow in discrete fracture networks.
Chapter 4

Time-Lapse Resistivity in Fractured Reservoirs

Electrical resistivity of a water-saturated rock depends on the salinity of the water as explained in Chapter 2. Thus, when injecting water elevated in salinity into a geothermal reservoir, the resistivity of the reservoir decreases. This chapter describes the relationship between fracture characteristics and the corresponding changes in time-lapse resistivity as a conductive fluid flows through the fractures in the reservoir. The intent was to investigate how this relationship could be utilized for fracture characterization. First, a fracture network with one injector and one producer was studied. The electric potential difference between the wells, corresponding to resistivity, changes as more and more fracture paths become filled with a conductive tracer. Then, a network with one injector, three producers and one test well was studied. The electric potential difference between all wells pairs was used to map the apparent resistivity of the field at different times. The same
network was also studied with the salinity of the injected water elevating with time to imitate the conductive fluid being reinjected.

4.1 Calculation of Time-Lapse Resistivity

The procedure used in this study to calculate time-lapse resistivity of fracture networks is illustrated in Figure 4.1. First, a flow simulator was used to simulate the flow of a NaCl solution through the reservoir. Then, for different time steps, Equations 3.23-3.26 were used to calculate the resistivity of the NaCl solution based on the concentration and temperature in the field. Archie’s law (Equation 2.1) was used to calculate the corresponding resistivity of the saturated fractures. The resistivity of the rock was set very high in the examples studied in this chapter so that the electric current flows only through the fractures. The resistivity of the rock and fractures was used in Equation 3.22 to calculate the corresponding permeability for simulating the electric field at different time steps. Then, a flow simulator was used to simulate the electric field, using the procedure demonstrated in Section 3.2. The voltage differences between the wells recorded over time correspond to the time-lapse resistivity.

4.2 Time-Lapse Resistivity in Fracture Network Ib

The time-lapse electric potential difference between wells, corresponding to time-lapse resistivity, was studied for the fracture network shown in Figure 4.2, referred to as Fracture Network Ib. The only difference between Fracture Network Ib and Fracture Network Ia, studied previously in Section 3.2.1, is the width of the fractures. In
Fracture Network Ia, the fracture width, $w$, was set as $2 \times 10^{-3}$ m but for Fracture Network Ib the width was assigned as a function of the fracture length $L$,

$$w = L \times 10^{-4}$$  \hspace{1cm} (4.1)

because fracture width has been shown to be larger for longer fractures [79, 86]. However, apart from a linear relationship between the fracture width and length, studies have also suggested that fracture width can be correlated with fracture length by a power-law [5]. The fracture permeability $k$ was defined by combining the Navier-Stokes solution for incompressible laminar flow of a Newtoninan fluid [59],

$$-\frac{dp}{dx} = \frac{12\mu}{hw^3}Q$$  \hspace{1cm} (4.2)

and Darcy’s law,

$$-\frac{dp}{dx} = \frac{\mu}{k}V$$  \hspace{1cm} (4.3)

where $dp/dx$ is the pressure gradient with $x$ a coordinate in the flow direction, $h$ is the fracture height, $\mu$ is the viscosity, $Q$ is the volume flow rate, and $V$ is the average velocity. Combining Equation 4.2 and Equation 4.3 yields the following cubic law for the fracture permeability $k$ [m$^2$],

$$k = \frac{w^2}{12}$$  \hspace{1cm} (4.4)

Other reservoir properties were the same as for Fracture Network Ia. The properties for the reservoir, flow simulation, and the electric simulation are summarized in Table 4.1. First, the flow of a conductive tracer through the fracture network was
studied and then the corresponding changes in resistivity distribution of the field were calculated.

4.2.1 Flow Simulation of Fracture Network Ib

The pores and fractures were modeled to be filled with water with NaCl concentration equal to 0.5 wt% before any tracer was injected into Fracture Network Ib. Then, water with NaCl concentration equal to 22 wt% was injected into the reservoir at $5.6 \times 10^{-2}$ kg/s and the production well was modeled to deliver against a bottom hole pressure of $10^6$ Pa. Closed (no flow) boundary conditions were used and the permeability of the matrix was set low so that the injected fluid would flow only through the fractures from the injector towards the producer. The EOS1 module in TOUGH2 was used with the Discrete Fracture Network (DFN) method introduced by Karimi-Fard et al. [55] to solve for the tracer flow. The computational grid was formed using Triangle [89]. The simulated tracer concentration at the wells is shown in Figure 4.3. The tracer reached the production well after about 0.02 days of injection. Then, the tracer concentration at the producer increased with time as more tracer was injected into the reservoir.

4.2.2 Electric Simulation of Fracture Network Ib

The electric potential of the reservoir was calculated at different times to study the changes in electrical potential difference between wells as the conductive fluid flows through the network. The same grid used for the flow simulation was also used for the electric field simulation. Equation 2.1 and Equations 3.23-3.26 were used to calculate the resistivity distributions at different time steps based on the temperature and
NaCl concentration of the fractures and the rock matrix. Then, for each resistivity distribution the electric field was calculated. The current was set as 1 A at the injector and as -1 A at the producer and the electric field was calculated using the EOS1 module in TOUGH2, using the analog between Ohm’s law and Darcy’s law as described in Section 3.2.1. The viscosity at the initial pressure and temperature conditions was $8.8899 \times 10^{-4}$ Pa s, which is the viscosity used in Equation 3.22 to calculate the permeability corresponding to the resistivity of the field. The injection rate in TOUGH2 input file was set as 1000 kg/s and the production rate as -1000 kg/s, to account for water density (Equation 3.21) which was close to 1000 kg/m$^3$ at the temperature and pressure conditions in the simulation. The simulation time was set as 10 days to ensure the simulation reached steady-state conditions. Then, the resulting pressure difference between the injector and the producer was the same as the voltage drop due to a current of 1 A at the injector and -1 A at the producer.

The electric potential difference between the injector and the producer is shown in Figure 4.4. The potential difference drops relatively quickly until about 0.25 days when it starts decreasing more slowly as a result of the entire fracture path from the injector to the producer becoming saturated with conductive tracer. Figure 4.3 shows that the tracer at the producer is increasing slower after 0.25 days and the tracer concentration is relatively close to the injected tracer concentration.

The relationship between the fractures and the time history of the electric potential can be made more visible by looking at the derivative of the potential difference, shown in Figure 4.5. The first peak is after about 0.02 days which is when the conductive tracer reaches the production well, as shown previously in Figure 4.3. Thus, the resistivity between the injector and the producer has decreased and a low-conductivity
path has been formed between the injector and the producer after 0.02 days, shown in Figure 4.6a-b. The electric current therefore flows through the low-conductivity path, causing the electric potential difference between the wells to drop. Other peaks can be seen in Figure 4.5, for example after approximately 0.08 days and approximately 0.18 days. The peak after 0.08 days corresponds to a new low-conductivity path formed to the left of the producer, shown in Figure 4.6c, and another path has been formed to the right after 0.18 days, shown in Figure 4.6d. The electric potential difference between the wells drops as the tracer decreases the resistivity of the field but the drop in potential difference is relatively larger when new conductive paths are formed. The fractures saturated with a conductive tracer can be compared to an electric circuit.

The total resistance, \( R_{total} \) of \( n \) resistors in the electric circuit in Figure 4.7 can be calculated as,

\[
\frac{1}{R_{total}} = \frac{1}{R_1} + \frac{1}{R_2} + \ldots + \frac{1}{R_n}
\]  

(4.5)

where \( R_1 \) to \( R_n \) are resistors connected in parallel. Thus, as more resistors are connected in parallel, the total resistance decreases. The voltage drop, \( V \), over the circuit can be calculated as,

\[
V = IR_{total}
\]  

(4.6)

As the total resistance decreases, the voltage drop decreases. Thus, when more paths from the injector to the producer in the fracture network are filled with the conductive tracer, more low-resistance paths connected in parallel are formed and the voltage drop, i.e. the electric potential difference between the wells, decreases. The peaks of
the derivative of the potential difference therefore correspond to the geometry of the fracture network.
Figure 4.1: Calculation of time-lapse electric potential between wells, corresponding to time-lapse resistivity.
### Table 4.1: Reservoir and simulation properties for Fracture Network Ib.

<table>
<thead>
<tr>
<th>Property</th>
<th>SI-units</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Reservoir</strong></td>
<td></td>
</tr>
<tr>
<td>Dimension</td>
<td>$30 \times 30 \times 1$ m$^3$</td>
</tr>
<tr>
<td>Fracture width</td>
<td>$L \times 10^{-4}$ m</td>
</tr>
<tr>
<td>Fracture porosity</td>
<td>0.9</td>
</tr>
<tr>
<td>Matrix porosity</td>
<td>0.1</td>
</tr>
<tr>
<td>Initial temperature</td>
<td>25°C</td>
</tr>
<tr>
<td>Initial tracer concentration</td>
<td>0.5 wt%</td>
</tr>
<tr>
<td><strong>Grid</strong></td>
<td></td>
</tr>
<tr>
<td>Max. fracture element size</td>
<td>0.5 m</td>
</tr>
<tr>
<td>Minimum angle</td>
<td>30°</td>
</tr>
<tr>
<td><strong>Flow simulation</strong></td>
<td></td>
</tr>
<tr>
<td>Matrix permeability</td>
<td>$1 \times 10^{-99}$ m$^2$</td>
</tr>
<tr>
<td>Fracture permeability</td>
<td>$w^2/12$</td>
</tr>
<tr>
<td>Flow rate at injector</td>
<td>$5.6 \times 10^{-2}$ kg/s</td>
</tr>
<tr>
<td>Enthalpy of injected water</td>
<td>$3.14 \times 10^5$ kJ/kg</td>
</tr>
<tr>
<td>Tracer wt% of inj. water</td>
<td>22 wt%</td>
</tr>
<tr>
<td>BHP at producer</td>
<td>$10^6$ Pa</td>
</tr>
<tr>
<td>Product. index at producer</td>
<td>$4 \times 10^{-12}$ m$^3$</td>
</tr>
<tr>
<td>Simulation time</td>
<td>12.5 hrs</td>
</tr>
<tr>
<td>Upper limit for time steps</td>
<td>1 s</td>
</tr>
<tr>
<td>Lower limit for time steps</td>
<td>100 s</td>
</tr>
<tr>
<td><strong>Electric Simulation</strong></td>
<td></td>
</tr>
<tr>
<td>Flow rate (current) at injector</td>
<td>1000 kg/s (1 A)</td>
</tr>
<tr>
<td>Flow rate (current) at producer</td>
<td>1000 kg/s (-1 A)</td>
</tr>
<tr>
<td>Initial pressure (voltage)</td>
<td>$10^6$ Pa (0 V)</td>
</tr>
<tr>
<td>Fluid density</td>
<td>1000 kg/m$^3$</td>
</tr>
<tr>
<td>Fluid viscosity</td>
<td>$8.889 \times 10^{-4}$ Pa s</td>
</tr>
<tr>
<td>Simulation time</td>
<td>10 days</td>
</tr>
<tr>
<td>Upper limit for time steps</td>
<td>0.1 s</td>
</tr>
<tr>
<td>Lower limit for time steps</td>
<td>100 s</td>
</tr>
</tbody>
</table>
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Figure 4.2: Fracture Network Ib with fractures shown in red.

Figure 4.3: Tracer history at the injector (blue) and at the producer (green) for Fracture Network Ib.
Figure 4.4: Potential difference between wells for Fracture Network Ib.

Figure 4.5: Derivative of the potential difference between the wells for Fracture Network Ib.
CHAPTER 4. TIME-LAPSE RESISTIVITY IN FRACTURED RESERVOIRS

Figure 4.6: Resistivity of Fracture Network Ib after a) 0.01 days, b) 0.02 days, c) 0.08 days and d) 0.18 days.

Figure 4.7: Electric circuit with resistors connected in parallel.
4.3 Time-Lapse Resistivity in Fracture Network II

Another Discrete Fracture Network (DFN) was modeled, this time with one injection well and three production wells. The network is shown in Figure 4.8. The width, \( w \), of the fractures was set as \( 10^{-2} \) m and the grid dimensions were \( 1000 \times 1000 \times 1 \) m\(^3\). The permeability of the fractures was determined as,

\[
k = \frac{w^2}{12}
\]  

(4.7)

Other reservoir and simulation properties are summarized in Table 4.2.

Figure 4.8: Fracture Network II.
### Table 4.2: Reservoir and simulation properties for Fracture Network II.

<table>
<thead>
<tr>
<th><strong>Reservoir</strong></th>
<th>Dimension: $1000 \times 1000 \times 1 \text{ m}^3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial temperature:</td>
<td>$25^\circ \text{C}$</td>
</tr>
<tr>
<td>Initial tracer concentration:</td>
<td>$0.05 \text{ wt}%$</td>
</tr>
<tr>
<td>Matrix porosity:</td>
<td>$0.1$</td>
</tr>
<tr>
<td>Fracture porosity:</td>
<td>$0.9$</td>
</tr>
<tr>
<td>Fracture width:</td>
<td>$10^{-2} \text{ m}$</td>
</tr>
</tbody>
</table>

| **Grid** | Maximum fracture element size: $15 \text{ m}$ |
| Minimum angle: | $30^\circ$ |

| **Flow simulation** | Matrix permeability: $1 \times 10^{-99} \text{ m}^2$ |
| Fracture permeability: | $w^2/12$ |
| Flow rate at injector: | $1.1 \times 10^{-2} \text{ kg/s}$ |
| Enthalpy of injected water: | $3.14 \times 10^5 \text{ kJ/kg}$ |
| Tracer wt% of injected water: | $9 \text{ wt}\%$ |
| Bottomhole pressure at producers: | $10^6 \text{ Pa}$ |
| Productivity index at producers: | $4 \times 10^{-12} \text{ m}^3$ |
| Simulation time: | 450 days |
| Length of time steps: | 100 s |
| Upper limit for time steps: | $1 \times 10^6$ |

| **Electric Simulation** | Matrix permeability (resistivity): $(9 \times 10^{95} \text{ ohm-m})$ |
| Flow rate (current) at injector: | $1 \times 10^6 \text{ kg/s (1000 A)}$ |
| Flow rate (current) at producer: | $1 \times 10^6 \text{ kg/s (-1000 A)}$ |
| Initial pressure (voltage): | $10^6 \text{ Pa (0 V)}$ |
| Fluid density: | $1000 \text{ kg/m}^3$ |
| Fluid viscosity: | $8.8899\times10^{-4} \text{ Pa s}$ |
| Simulation time: | 10 days |
| Length of time steps: | 0.1 s |
| Upper limit for time steps: | $1 \times 10^3 \text{ s}$ |
4.3.1 Flow Simulation of Fracture Network II

A NaCl solution of 9 wt% was injected into the reservoir at the rate of $1.1 \times 10^{-2}$ kg/s and the production wells were modeled to deliver against a bottom hole pressure of $10^6$ Pa. Closed (no-flow) boundary conditions were used and the fractures were initially assumed to be filled with water with $5 \times 10^{-2}$ wt% NaCl concentration. As for the previous case, the Discrete Fracture Network (DFN) method [55] was used with the EOS1 module in TOUGH2 to solve for the tracer flow. The computational grid was formed using Triangle [89] where the maximum size for fracture elements was set as 15 m and the minimum angle size was set as $30^\circ$. Figure 4.9 shows the tracer return curves at the producers and the injected tracer concentration after simulating the flow for 450 days. The conductive fluid travels fastest towards Producer 1 because of the relatively straight path between the injector and Producer 1 (shown in Figure 4.8). The tracer return curves indicate more tortuous flow paths between the injector and Producer 2, and the injector and Producer 3.

4.3.2 Electric Simulation of Fracture Network II

The electric potential differences between all well pairs were calculated using the same procedure as in the previous example, and explained in Chapter 3.2.1. The electric current was set as 1 A at one well and as -1 A at another and the potential difference between them was calculated using the EOS1 module in TOUGH2. The injection/production rate (analogous to the current) was multiplied by 1000 to account for the water density. Then, the flow rate was multiplied by 1000 again to produce sufficient digits for the electric results. Thus, the pressure results were divided by 1000 to obtain the electric voltage results for ±1 A current at the wells.
Then, the same procedure was done to calculate the electric potential difference between all other well pairs. A test well that was used for measurements only was assumed to be located in a fracture in the middle of the reservoir between all the wells to get more measurement points.

The electric potential differences between the wells were used to solve for the apparent resistivity, $\rho_a$ [ohm-m], using the following version of Ohm’s law,

$$\rho_a = \frac{\Delta V}{I} K$$

(4.8)

where $\Delta V$ [V] is the potential difference between the wells, $I$ [A] is the intensity of the current flowing through the network, and $K$ [m] is a geometric factor. In resistivity studies in geophysics, the total current is assumed to flow away from or
toward each electrode across the surface of a half sphere (Figure 2.1), or a whole sphere if electrodes are placed underground (Figure 2.2). Here, the current flow is significantly different, because the rock is a good insulator so the current flows only through the thin fractures. Therefore, if a conventional geometric factor which only depends on the electrode spacing is used, the apparent resistivity values calculated would be very different from the true resistivity values. The volume considered for electrodes placed far apart (i.e. defined by the sphere-shaped flow paths) would be much larger than for electrodes placed closer to each other, while the true increase in fracture flow path volume because of a larger distance between electrodes would be relatively small. Finding the true geometric factor is a difficult task because the fracture characteristics are unknown, but in order to find a suitable geometric factor the potential differences between the wells before any tracer has been injected is used. It is assumed that all the wells are connected with fractures and that the resistivity of the fractures is $\rho = 36.59 \text{ ohm-m}$, corresponding to fractures with porosity 0.9 and filled with 9 ohm-m water. Therefore, all the current flows through the fractures because of the high resistivity of the rock. The geometric factor, $K [m]$, between each well pair is then calculated using Equation 4.8 as well as the assumed resistivity of the water-filled fractures, the known injected current, and the measured potential differences between the wells. If the fracture network were to be expressed as a simplified electric circuit, this geometric factor would represent the cross-sectional area of the wire, divided by its length, i.e. the length of the current path. Therefore, the geometric factor corresponds to the current flow path and could possibly be used to gain information about the fracture network. Here, the geometric factor is used to
calculate the apparent resistivity for the fractures, which is used for comparison at different time steps to locate where the conductive fluid is flowing.

The apparent resistivity was mapped by kriging and the general exponential-Bessel variogram was used to fit the data. Kriging is an optimal method for estimation of unknown values within known data points and was developed by Krige [62]. In this case, very few data points are known because of the scarcity of measurement points, i.e. few wells, but mapping by kriging helps illustrate the changes in resistivity as conductive tracer is injected into the reservoir. Figure 4.10 illustrates the changes in the apparent resistivity between the wells, mapped by kriging, as the conductive fluid flows through the fracture network.

At the beginning, all the fractures are filled with water and therefore have the same resistivity, equal to 36.59 ohm-m. After 24 days of injection, the apparent resistivity has decreased in the upper part of the figure. Then, after 200 days of injection, as well as after 450 days, the upper right corner has the lowest resistivity and it has changed significantly in the lower right corner as well. These changes in resistivity indicate good fracture connection from the injector to Producer 1, then from Producer 1 to Producer 3, but lower connection towards Producer 2.

Figure 4.11 shows the true resistivity distribution after 70 days, which is in accordance with previous results. The fracture path between Producer 2 and Producer 3 is the last one to fill up with conductive tracer, which causes high potential difference between these producers and therefore high apparent resistivity in Figure 4.10. Considering that the changes in apparent resistivity with time gave good information about the connection between the wells, the time history of the electric potential should be useful for fracture characterization.
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4.3.3 Time-Lapse Resistivity in Fracture Network II with Re-Injected Conductive Fluid

In reality, the produced fluid is likely to be reinjected into the reservoir, causing the injected fluid to be elevated in NaCl concentration continuously with time due to the separation of steam. Therefore, the same case was studied but with the injected

Figure 4.10: Apparent resistivity [ohm-m] for Fracture Network II calculated from potential measurements between wells after a) 24 days, b) 70 days, c) 200 days and d) 450 days.
Figure 4.11: Resistivity [ohm-m] of Fracture Network II after 70 days of injection.

tracer concentration increasing in steps after 100 days. Figure 4.12 shows the injected tracer concentration and the tracer return curves for the three producers.

The tracer return curves indicate good connection between the injector and Producer 1, but due to weaker connections towards Producer 2 and Producer 3 the tracer concentration in these wells does not reach the injected concentration. As a result, the contrast in resistivity between the strongest and the weakest connections remains high (shown in Figure 4.13) because the majority of the tracer will always be flowing through the best-connected flow path from the injector to the producers. In the previous case, where the injected water had a constant NaCl concentration, the weaker-connected paths became greatly saturated as well once all the
stronger-connected paths were fully saturated with tracer. Therefore, the connection between the injector and Producer 2 could be observed after about 200 days of injection, while the mapped apparent resistivity at the same time for the reinjection case does not indicate the same connection, shown in Figure 4.13 (left). However, both examples gave some good information about the fracture connections between the wells and indicated that the time histories of the apparent resistivity between the wells could be used for fracture characterization.
4.4 Summary

This chapter showed how the changes in salinity of the fluid in geothermal reservoirs affected the electric potential difference between the wells. As more connected paths from the injector towards the producers were filled with conductive tracer, the electric potential dropped. Therefore, the time-history of the electric potential could give information about the fracture network. In the first example, one injector and one producer were modeled and changes in electric potential between the wells as more paths were concentrated with tracer could be seen clearly by looking at the derivative of the electric potential. The peaks in the derivative corresponded to the times of new highly conductive paths being formed. In the second example, one injector and three producers were modeled. Kriging was used to map the apparent resistivity between all well pairs as tracer was injected into the reservoir to locate the most connected areas. The same example was also used where reinjected fluid was elevated in NaCl.
concentration with time. Results showed how the changes in electric potential due to injection of conductive fluid could indicate connected fractures in the reservoirs.
Chapter 5

Fracture Characterization Indices

The complex multiscaled character of fracture patterns in fractured reservoirs and their high degree of heterogeneity makes fracture characterization very difficult. Faults and fractures have been modeled in reservoirs where fractures are detected using the geophysical exploration methods described in Chapter 2, but such methods often fail to detect the location and orientation of smaller fractures that might be contributing to the flow. Characterizing every fracture in the reservoir and creating an exact fine-scale model where all fractures are resolved is not feasible so finding a way to describe the fracture flow behavior sufficiently is important.

This chapter addresses the issue of describing the important fracture characteristics with a fracture characterization index. It is important that the index is representative of the fluid movement through the reservoir so it can be used to model and predict energy extraction in the reservoir accurately. The four fracture characterization indices discussed in this chapter are Fracture Density Parameter, Fractal Dimension, Fractional Connected Area, and Connectivity Index. Other methods commonly used to describe the flow behavior in fractured reservoirs
include upscaling physical properties of the fracture networks to numerical blocks but this study focused on Discrete Fracture Network (DFN) simulations to avoid volume averaging that would not represent the fracture flow system accurately. Generally, discrete fracture networks can capture a wider range of transport phenomena. For example, the flow behavior in a matrix with a small number of large-scale fractures which may dominate the flow is represented better with a Discrete Fracture Network (DFN) because the fracture permeability would be underestimated when averaged over grid blocks.

5.1 Fracture Density Parameter

Fracture density is a general term that describes the intensity of fractures within a specific area of rock. It can be defined by the number of fractures per unit length or volume. Fracture density is often measured directly from field data such as on a core sample or on a borehole wall. In outcrops, fracture density is measured against scan-lines (imaginary lines) along which the intersection points with fractures are counted. Figure 5.1 illustrates a well considered as a scan-line of the subsurface. Higher fracture density improves the chances of interconnection and therefore indicates better connectivity in the reservoir.

Fracture density can also be measured in terms of distance, i.e. spacing between fractures. Then, instead of counting the number of fractures, the depth value at which the fracture crosses the scan-line is listed. That way, the distance between the fractures, i.e. the fracture spacing, can be examined as well. Plotting the downhole frequency with depth can help making a quick assessment of the formation boundaries.
The fracture density parameter, $C$, is a fracture characterization index related to the fracture density [103],

$$C = \frac{m}{\cos \theta_i (1 - \ln L_{\text{min}})}$$  \hfill (5.1)

where $m$ is the linear fracture density in terms of the number of fractures per unit length, $\theta_i$ is the orientation from horizontal of the $i$th set of fractures, $\overline{\cos \theta_i}$ is the average of all $\cos \theta_i$, and $L_{\text{min}}$ is the smallest fracture length studied. Watanabe and Takahashi [103] suggested using the fracture density parameter $C$ to predict hydraulic properties of fractured reservoirs and showed that the transmissivities in geothermal reservoirs significantly depend upon the fracture density of the rock mass. They
used the fracture density parameter to model fracture networks using a Monte Carlo (MC) simulation and calculated the connectivities between wells. The transmissivities were plotted as a function of the fracture density parameter and results showed that the parameter could be used to predict the transmissivities in geothermal reservoirs. Figure 5.2 shows examples of fracture networks generated by Watanabe and Takahashi [103] for different values of the fracture density parameter. The figures demonstrate that the fracture density parameter influences the fracture network patterns strongly.

Other studies have been performed where the fracture density parameter has been used to provide a descriptive measure of the hydraulic properties in fractured rock [10]. Leucci and Girogi [66] carried out experimental studies to investigate the effects of compressional waves $V_p$ and shear waves $V_s$ on rock fractures using fracture characterization indices including the fracture density parameter. They concluded that the seismic velocities decrease with higher values of the fracture density parameter and could therefore be used to indicate high transmissivity zones.
5.2 Fractal Dimension

A number of geological investigations have confirmed that fracture networks in the subsurface can be described by fractal geometry. Studies have analyzed both the spatial fractal behavior \([6,36,44,64]\) and the fracture length distribution \([13,40]\). This fractal behavior has been observed in natural fracture patterns at different length
scales and it has provided a generic relationship between fractures at all scales which can be described by the fractal dimension.

5.2.1 Spatial Distribution

The fractal dimension for spatial distribution can be determined using the box-counting method [6]. A sequence of grids with different box sizes is placed over a map of fractures and the number of boxes that include fracture center points is counted. The spatial fractal dimension \( D \) within an \( l \times l \) square domain can be represented by the following fractal equation,

\[
N(r) r^D = 1
\]

or equivalently,

\[
D = \lim_{r \to 0} \frac{\log N(r)}{\log(1/r)}
\]

where \( N(r) \) is the number of boxes of size \( r \) that include the center point of fractures, and \( r = l/k \) (\( k = 1, 2, 3, \ldots \)). Thus, the fractal dimension \( D \) is a measure of the spatial distribution of the fractures. Barton and Larsen [6] demonstrated how the fractal dimension is equal to the slope of a straight-line fitted to the points of \( N(r) \) and \( 1/r \) plotted on logarithmic axes, as illustrated in Figure 5.3. The differences in spatial fracture distribution for fracture networks with spatial fractal dimension \( D = 1.0 \) and with \( D = 1.8 \) are demonstrated in Figure 5.4. The fracture connectivity for the network with higher fractal dimension is considerably better because of fractures covering a larger part of the field.
The spatial fractal dimension can also be estimated using different techniques such as the sand-box technique. In the sand-box method, the number of fracture center points located inside a circle with a specific center is counted. Then, the size of the circle is increased and the same procedure continued. Similar to the box-counting method, the number of fracture center points is plotted against the size of the circle on logarithmic axes and the slope of the straight line yields the fractal dimension [15]. The sand-box technique measures different fractal characteristics and might yield different values than the box-counting method [4].

In addition, the spatial fractal dimension can be calculated using the distribution of fractures, or fracture intersections, instead of the fracture center points. Then, for the box-counting method, the number of fractures or the number of fracture intersections inside different sized boxes is counted. Similarly, for the sand-box
method, the number of fractures or fracture intersections inside different sized circles is counted.

5.2.2 Length Distribution

Several field studies performed on fault systems at different length scales have demonstrated that the fracture lengths can follow a power-law distribution. The length distribution can be described by the following fractal equations [71],

\[ N(L) = BL^{-a} \]  

\[ a = \lim_{L \to 0} \frac{\log N(L)}{\log(1/L)} \]  

where \( a \) is the fractal dimension of the fracture length distribution and \( N(L) \) is the number of fractures with lengths larger or equal to \( L \). Thus, \( L = L_{\text{max}} \) when \( N(L) = 1 \) where \( L_{\text{max}} \) is the maximum fracture length. \( B \) is a coefficient of proportionality that Nakaya et al. [71] defined as,

\[ B = (L_{\text{max}})^a \]  

Gudmundsson [40] studied the geometry of tectonic fractures on the Reykjanes Peninsula in southwest Iceland and demonstrated that the length distribution was approximated reasonably well by Equation 5.4. A theoretical and numerical study of the connectivity of faults following a power-law length distribution was also presented by Bour and Davy [13]. They demonstrated that the connectivity is strongly dependent on the fractal dimension \( a \), as illustrated in Figure 5.5. For \( a = 3.5 \) (Figure 5.5a) the cluster is made of quite small faults while for \( a = 2.5 \) (Figure
5.5b) the proportion of small and large faults is similar. Bour and Davy [13] identified different connectivity regimes that depended on the fractal dimension of the fracture length distribution.

Watanabe and Takahashi [103] presented a fractal geometry based approach using the fracture density parameter described in a previous section. In their studies, the fractal relation between fracture length $L$ and the number of fractures $N(L)$ whose length is larger or equal to $L$ was expressed by,

$$N(L) = CL^{-a}$$  \hspace{1cm} (5.7)

where $C$ is the fracture density parameter. This method was applied to Kakkonda geothermal field in Japan to characterize fracture networks and the results suggested that this modeling procedure provides a reasonable means for fracture characterization in geothermal reservoirs [99].

Despite a large number of analyses demonstrating fractal behavior in subsurface fracture patterns, it is also important to note discussions about the statistical relevance of power-law models [11, 20, 82]. Achieving a robust statistical analysis on limited data sets that are often obtained over only one order of magnitude may be difficult [29]. In addition, not all fracture patterns can be characterized by a fractal geometry [76]. Bonnet et al. [11] concluded that a single fractal dimension could not completely define a fracture system and that the fractal dimension of other parameters than the spatial distribution needs to be considered as well, such as length, density, orientation, and aperture.
Figure 5.4: A fractal fracture network with spatial fractal dimension equal to a) $D = 1.0$ and b) $D = 1.8$. 
Figure 5.5: Clusters of two-dimensional fault networks presented by Bour and Davy [13] with fractal dimension of the length distribution a) $a = 3.5$ and b) $a = 2.5$. 
5.3 Fractional Connected Area

Stauffer [98] quantified fracture connectivity by the size of a group of linked fractures, known as a ‘cluster’. The cluster size is measured by the length of the largest connected group of fractures as a proportion of the total fracture length in the network [76]. Alternatively, the connectivity can be defined by the fraction of the total area that is connected by clusters, as described by Ghosh and Mitra [37]. They defined Fractional Connected Area (FCA) as the summed area of all clusters within a fracture network divided by the total sample area,

\[
\text{FCA} = \frac{\text{Summed area of all fracture clusters}}{\text{Total sample area}} \tag{5.8}
\]

The area of a cluster is delineated by the simplest polygon around the extremities of a fracture cluster, as demonstrated in Figure 5.6. Ghosh and Mitra [37] concluded that FCA combined with a distribution of cluster sizes provides a complete measure of the connectivity of fractures within the system. They assumed that the fracture sets had similar apertures so that the contribution of fractures to the connectivity was dependent only on their lengths and densities. The distribution of cluster sizes depends on the number of fracture sets and the density of each fracture sets. The importance of the distribution of cluster sizes is demonstrated by Ghosh and Mitra [37] in Figure 5.7 where two different networks with the same Fractional Connected Area (FCA) are shown along with the distribution of cluster sizes within each network. The fracture networks are quite different despite the FCA being the same.

The fractional connected area alone defines the probability of a drilled well encountering a connected fracture network within the field being studied. FCA is
also a good indicator of the overall fracture density and does not relate the cluster size to only the connectivity within the largest cluster. In fractured reservoirs, the connected area has high influence on the heat and mass transport in the system. Larger connected areas result in good connection and wider connected range with fluid traveling faster towards the producers, while fewer or smaller connected areas result in a poorer connection.
Figure 5.7: A figure by Ghosh and Mitra [37] demonstrating a) a fracture network and connected areas for Case 1, b) a fracture network and connected areas for Case 2, c) a histogram of distribution of the cluster area for Case 1, and d) a histogram of distribution of the cluster area for Case 2.
5.4 Connectivity Index

Xu et al. [107] demonstrated how a Connectivity Index (CI) can be used to quantify fracture connectivity in geothermal reservoirs. The connectivity index, $\tau$, measures the probability of a connection between two arbitrary points, $x$ and $y$, (e.g. an injector and a producer) within a region $R$ of a fracture system,

$$\tau(x, y) = P(x \leftrightarrow y), \forall x, y \in R$$ (5.9)

where $x \leftrightarrow y$ represents a connection between points $x$ and $y$. A support is defined as the smallest unit for the index evaluation. Thus, if $x_v$ and $y_v$ are connected, there exists a pathway, or pathways, through the fracture network intersecting the smallest unit (the support), $v$, centered at points $x$ and $y$. Then, the connectivity index between $x$ and $y$, based on support $v$ is defined as,

$$\tau_v(x, y) = P(x_v \leftrightarrow y_v), \forall x_v, y_v \in R$$ (5.10)

Figure 5.8 shows how Xu et al. [107] demonstrated a connection between $x_v$ and $y_v$ while there is no connection between $x_v$ and $z_v$.

The connectivity between two locations can be described by an indicator variable, $\nu_v(x, y)$,

$$\nu_v(x, y) = \begin{cases} 
1 & \text{if } x_v \leftrightarrow y_v, \forall x_v, y_v \in R \\
0 & \text{otherwise}
\end{cases}$$ (5.11)

Then, if multiple fracture realizations are generated for a specific fracture model using Monte Carlo (MC) simulations, the connectivity index between a support centered at $x$ and a support centered at $y$ can be calculated as,
Figure 5.8: A figure by Xu et al. [107] demonstrating a connection between points $x_v$ and $y_v$ but no connection between points $x_v$ and $z_v$.

\[
\hat{\tau}(x, y) = \frac{1}{N(MC)} \sum_{i=1}^{N} v_i^v(x, y) \tag{5.12}
\]

where $\hat{\tau}(x, y)$ is the estimator of $\tau(x, y)$ and $N(MC)$ is the number of Monte Carlo (MC) simulations.

Xu et al. [107] estimated the connectivity index for two discrete fracture models using Monte Carlo (MC) simulations and concluded that the connectivity index provides an effective means of describing the possible connections through fractures between two points. In addition, Fadakar et al. [28] demonstrated how fracture size and aperture can be incorporated into the evaluation of the connectivity index to determine more reliable flow paths in the fracture network. A weighting factor, $W$, was used,
\[ W = (\sum \frac{1}{L_i})^{-1} \sum \frac{w_i}{L_i} \] (5.13)

where \( w \) is the aperture and \( L \) is the length of the fractures connecting the two supports being studied. The connectivity indices were weighted by \( W \) and the results showed that the accuracy of the flow characteristics of the fracture network were improved by incorporating the length and aperture of the fractures into the connectivity index.

### 5.5 Summary

In this chapter, four fracture characterization indices describing the character of fractured reservoirs were summarized. A fracture density parameter that depends on the fracture density of the system and provides a descriptive measure of hydraulic properties in fractured rock was described. Then, a number of studies were outlined that have confirmed that natural fracture patterns can be described with a fractal dimension. This chapter described the fractal behavior of spatial and length distributions of fractures. Fractional connected area was defined and studies have shown that fractional connected area combined with a distribution of cluster sizes provides a complete measure of the connectivity of fractures within the fracture system. In addition, a connectivity index that has also been used to quantify fracture connectivity in geothermal reservoirs was described. Following chapters will describe how these various fracture characterization indices were investigated as candidates for use in inverse analysis of fracture networks in geothermal reservoirs.
Chapter 6

Inverse Analysis

This chapter outlines the general concepts of the inverse analysis used in this study for fracture characterization. A library of Discrete Fracture Networks (DFNs) was generated and a series of simulations were conducted using General Purpose Research Simulator (GPRS) [16]. GPRS was used to solve both the flow of a conductive tracer through the fracture networks and the time-varying electric fields. Thus, the fracture network library consists of fracture networks, tracer return curves at the producers for all the networks and the time-histories of the electric potential difference between all well pairs.

In the inverse analysis, the correlation between the fracture network characteristics and the corresponding time-lapse electric field, previously discussed in Chapter 4, was utilized. The inverse procedure compares the time-lapse electric data for a geothermal reservoir to the electric data for fracture networks in the library of networks to find the best match. In order to use the best match to estimate the character of the geothermal reservoir, the fracture characterization indices discussed in Chapter 5 were studied. Two of the indices were chosen to describe the character of the fracture networks for
the inverse analysis in this study; the fractal dimension and the fractional connected area.

6.1 Library of Fracture Networks

A library of two-dimensional Discrete Fracture Networks (DFNs) representing fractured geothermal reservoirs was generated. The goal was to model various fracture networks, their tracer flow behavior as well as their corresponding changes in electric fields and use this data with inverse modeling to characterize fractures in geothermal reservoirs. This section describes the reservoir properties of the fracture networks in the library of networks as well as the simulation properties for the flow and electric simulations.

6.1.1 Reservoir Properties

The fracture networks were modeled using a Discrete Fracture Network (DFN) approach by Karimi-Fard et al. [55] and the fields were discretized into triangular elements using Triangle [89]. Section 5.2 described how a number of geological investigations have shown that spatial fracture distributions and fracture length distributions can be described by fractal geometry [6, 13, 36, 40, 44, 64]. Thus, the fractures modeled in this study were assumed to follow a spatial fracture distribution described by the box-counting approach [6],

\[ N(r)r^D = 1 \]  \hspace{1cm} (6.1)

or equivalently,


\[ D = \lim_{r \to 0} \frac{\log N(r)}{\log(1/r)} \]  

(6.2)

where \( D \) is the spatial fractal dimension, \( N(r) \) is the number of boxes of size \( r \) that include the center point of fractures, \( r = l/i \) \((i=1,2,3,\ldots)\), and \( l \) is the length of the square domain. Similarly, the fractal fracture length distribution was assumed to be fractal,

\[ N(L) = BL^{-a} \]  

(6.3)

or equivalently,

\[ a = \lim_{L \to 0} \frac{\log N(L)}{\log(1/L)} \]  

(6.4)

where \( a \) is the fractal dimension of the fracture length distribution and \( N(l) \) is the number of fractures with lengths larger or equal to \( L \). Thus, \( L=L_{\text{max}} \) when \( N(L)=1 \) where \( L_{\text{max}} \) is the maximum fracture length. The proportionality coefficient \( B \) was defined the same way as defined by Nakaya et al. [71],

\[ B = (L_{\text{max}})^a \]  

(6.5)

A total of 600 discrete fracture networks with fractal dimensions ranging from \( D = 1.0 \) to 1.8 with 0.1 increments were created using a method described by Nakaya et al. [71], demonstrated in Figure 6.1. The positions of the fracture centers were selected according to the spatial fractal dimension \( D \). At the \( i \)th iteration \((i=1,2,3,\ldots)\), \( 2^{Di} \) boxes (rounded to the nearest integer) out of \( 4^i \) equally sized boxes were selected randomly. Thus, at the first iteration for \( D = 1.4 \), \( 2^{1.4 \times 1} = 3 \) boxes were selected.
Then, the procedure was repeated for $i = 2$, but only the boxes selected during the previous iteration were available for selection in the successive iterations. In this study, four iterations were conducted and then the midpoints of all the boxes chosen during that last iteration were defined as fracture centers. Figure 6.2 shows an example of a fractal fracture network with spatial fractal dimension $D = 1.4$.

The dimension of the reservoirs was set as $1000 \times 1000 \times 1 \, \text{m}^3$ and the fracture lengths were determined according to the fractal dimension of the length distribution $a$ and the maximum fracture length $L_{\text{max}}$ using Equations 6.3-6.5. The fractal dimension of the length distribution was defined as $a = 2.4$ and the maximum fracture length was set as $L_{\text{max}} = 600 \, \text{m}$. The angles normal to the fractures were chosen to have two different distributions, both equally as likely to be chosen. The angles had a normal distribution with the mean either as $45^\circ$ or as $135^\circ$, and with a standard deviation of $5^\circ$. The fracture width was defined by,

$$w = ML^n \quad (6.6)$$

where $w$ is the width and $M$ is a constant. Olson [79] described how this power law equation was used to fit various fracture datasets of different sizes, usually with $n = 0.4$. Here, $n$ was set as $0.4$ and $M$ as $0.002 \, \text{m}^{3/5}$. Other reservoir properties as well as parameters for the flow and electric simulations are summarized in Table 6.1.
Figure 6.1: A figure by Nakaya et al. [71] demonstrating an algorithm to generate fracture networks with fractal fracture distribution.
Figure 6.2: Example of a fractal fracture network with spatial fractal dimension $D = 1.4$. 


### Chapter 6. Inverse Analysis

Table 6.1: Reservoir and simulation properties for the fracture network library.

<table>
<thead>
<tr>
<th>Reservoir</th>
<th>SI-units</th>
<th>Oil-field units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dimension:</td>
<td>$1000 \times 1000 \times 1 \text{ m}^3$</td>
<td>$3281 \times 3281 \times 3.281 \text{ ft}^3$</td>
</tr>
<tr>
<td>Fractal dimension (spatial):</td>
<td>1.0-1.8</td>
<td>1.0-1.8</td>
</tr>
<tr>
<td>Fractal dimension (length):</td>
<td>2.4</td>
<td>2.4</td>
</tr>
<tr>
<td>Fracture orientations (mean):</td>
<td>$45^\circ$, $135^\circ$</td>
<td>$45^\circ$, $135^\circ$</td>
</tr>
<tr>
<td>Maximum fracture length:</td>
<td>600 m</td>
<td>1968.5 ft</td>
</tr>
<tr>
<td>Fracture width:</td>
<td>$0.002 \times L^{0.4} \text{ m}$</td>
<td>$0.006562 \times L^{0.4} \text{ ft}$</td>
</tr>
<tr>
<td>Fracture porosity:</td>
<td>0.9</td>
<td>0.9</td>
</tr>
<tr>
<td>Matrix porosity:</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>Initial temperature:</td>
<td>25°C</td>
<td>536.67 R</td>
</tr>
<tr>
<td>Initial tracer concentration:</td>
<td>0.05 wt%</td>
<td>0.05 wt%</td>
</tr>
</tbody>
</table>

| Grid | | |
| Max. fracture element size: | 61 m | 200 ft |
| Minimum angle: | 25° | 25° |

| Flow simulation | | |
| Matrix permeability: | $9.869 \times 10^{-11} \text{ m}^2$ | $1 \times 10^5 \text{ md}$ |
| Fracture permeability: | $w^2/12$ | $w[m]^{2/12} \times 1.0133 \times 10^{15} \text{ md}$ |
| Flow rate at injector: | 10 kg/s | 5434.3 STB/day |
| Tracer wt% of inj. water: | 22 wt% | 22 wt% |
| BHP at producers: | $10^6 \text{ Pa}$ | 145.0377 psi |
| Product. index at producers: | $4 \times 10^{-12} \text{ m}^3$ | 13123.36 md-ft |
| Simulation time: | 8640000 s | 100 days |
| Upper limit for time steps: | 8640 s | 0.1 days |
| Lower limit for time steps: | 0.864 s | $1 \times 10^{-5}$ days |

| Electric Simulation | | |
| Flow rate (current) at injector: | 10 kg/s (1 A) | 5434.3 STB/d (1 A) |
| BHP (current) at producers: | $10^6 \text{ Pa}$ (-1 A) | 145.0377 psi (-1 A) |
| Product. index at producers: | $4 \times 10^{-12} \text{ m}^3$ | 13123.36 md-ft |
| Initial pressure (voltage): | $10^6 \text{ Pa}$ (0 V) | 145.0377 psi (0 V) |
| Fluid density: | 1000 kg/m$^3$ | 62.4 lbm/ft$^3$ |
| Fluid viscosity: | $8.889 \times 10^{-4} \text{ Pa s}$ | 0.8889 cp |
| Simulation time: | 86400 s | 1 day |
| Upper limit for time steps: | 69120 s | 0.8 days |
| Lower limit for time steps: | 86.4 s | $1 \times 10^{-3}$ days |
6.1.2 Flow Simulation

General Purpose Research Simulator (GPRS) [16] was used to simulate the flow of a conductive tracer through the fractured geothermal reservoirs in the library of fracture networks. GPRS is a multiple purpose research simulator with a large variety of features such as structured and unstructured grids, and black-oil and fully compositional models. GPRS does not have an updated tracer flow model but geothermal systems were simulated using a fully implicit black-oil model with injected water representing the conductive tracer and the properties of oil defined the same as the properties for water. Oil-field units are used in GPRS so the parameters were converted from SI units to oil-field units using the conversion factors shown in Table 6.2.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Conversion</th>
<th>Oil-field units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dimension:</td>
<td>$[m] \times 3.2808$</td>
<td>ft</td>
</tr>
<tr>
<td>Permeability:</td>
<td>$[m^2] \times 1.0133 \times 10^{15}$</td>
<td>md</td>
</tr>
<tr>
<td>Flow rate:</td>
<td>$[kg/s] \times 5.4343 \times 10^2$</td>
<td>STB/day</td>
</tr>
<tr>
<td>Pressure:</td>
<td>$[Pa] \times 1.1450 \times 10^{-4}$</td>
<td>psi</td>
</tr>
<tr>
<td>Productivity index:</td>
<td>$[m^3] \times 3.3243 \times 10^{15}$</td>
<td>md ft</td>
</tr>
<tr>
<td>Density:</td>
<td>$[kg/m^3] \times 0.0624$</td>
<td>lb/ft$^3$</td>
</tr>
<tr>
<td>Temperature:</td>
<td>$([^\circ C] + 273.15) \times 9/5$</td>
<td>R</td>
</tr>
</tbody>
</table>

The tracer return curves calculated using the black-oil model in GPRS were verified via a comparison to TOUGH2 for Fracture Network Ib, shown in Figure 6.3 and studied previously in Section 4.2. The reservoir and flow properties are summarized in Table 6.3 where the SI units refer to the values used in TOUGH2 and oil-field units refer to the values used in GPRS. The size of the grid and time steps were set smaller for the TOUGH2 flow simulation than the GPRS simulation.
because of numerical errors that occurred when using TOUGH2 with discrete fracture networks. The TOUGH2 flow simulation could only be run for 0.05-0.2 days at a time before the solution became unstable and the following error occurred: 'run-time error M6201: MATH - sqrt: DOMAIN error', which indicates that the program might for instance be taking a square root of a negative value. Thus to avoid the error, the TOUGH2 flow simulation had to be carried out in 11 steps where the initial properties at each simulation were set as the properties where the previous simulation stopped.

![Fracture Network Ib with fractures shown in red.](image)

**Figure 6.3:** Fracture Network Ib with fractures shown in red.

Tracer was injected at a rate of 0.015 kg/s and the production well was modeled to deliver against a bottom-hole pressure of $10^6$ Pa. The permeability of the matrix was defined to be low so that the tracer would flow only through the fractures. The
Table 6.3: Reservoir and simulation properties for Fracture Network Ib.

<table>
<thead>
<tr>
<th></th>
<th>SI units</th>
<th>Oil-field units</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Reservoir</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dimension</td>
<td>$30 \times 30 \times 1 \text{ m}^3$</td>
<td>$98.42 \times 98.42 \times 3.28 \text{ ft}^3$</td>
</tr>
<tr>
<td>Fracture width</td>
<td>$L \times 10^{-4} \text{ m}$</td>
<td>$3.2808 L \times 10^{-4} \text{ m}$</td>
</tr>
<tr>
<td>Fracture porosity</td>
<td>0.9</td>
<td>0.9</td>
</tr>
<tr>
<td>Matrix porosity</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>Initial temperature</td>
<td>25°C</td>
<td>536.67 R</td>
</tr>
<tr>
<td>Initial tracer concentration</td>
<td>0.5 wt%</td>
<td>0.5 wt%</td>
</tr>
<tr>
<td><strong>Grid</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Max. fracture element size</td>
<td>0.5 m</td>
<td>9.84 ft</td>
</tr>
<tr>
<td>Minimum angle</td>
<td>30°</td>
<td>30°</td>
</tr>
<tr>
<td><strong>Flow simulation</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Matrix permeability</td>
<td>$1 \times 10^{-99} \text{ m}^2$</td>
<td>$1.013 \times 10^{-84} \text{ md}$</td>
</tr>
<tr>
<td>Fracture permeability</td>
<td>$w^2/12$</td>
<td>$w[m]^2/12 \times 1.013 \times 10^{15} \text{ md}$</td>
</tr>
<tr>
<td>Flow rate at injector</td>
<td>0.015 kg/s</td>
<td>8.15 STB/day</td>
</tr>
<tr>
<td>BHP at producers</td>
<td>$10^6 \text{ Pa}$</td>
<td>145,0377 psi</td>
</tr>
<tr>
<td>Product. index at producers</td>
<td>$4 \times 10^{-12} \text{ m}^3$</td>
<td>13123.36 md-ft</td>
</tr>
<tr>
<td>Simulation time</td>
<td>69120 s</td>
<td>0.8 days</td>
</tr>
<tr>
<td>Upper limit for time steps</td>
<td>100 s</td>
<td>$2 \times 10^{-2}$ days</td>
</tr>
<tr>
<td>Lower limit for time steps</td>
<td>1 s</td>
<td>$1 \times 10^{-4}$ days</td>
</tr>
</tbody>
</table>

Permeability of the fractures $k \left[ \text{m}^2 \right]$ was defined by,

$$ k = \frac{w^2}{12} \tag{6.7} $$

where $w \left[ \text{m} \right]$ is the width of the fractures. Figure 6.4 shows the tracer results at the producer as a fraction of the injected tracer. GPRS and TOUGH2 gave a very similar solution for the tracer return curve, thus verifying that GPRS could be used in this study to solve for the tracer flow.

GPRS was used to simulate the flow of a tracer from an injector towards three producers for all the fracture networks in the library of networks. The location of the wells is illustrated in Figure 6.2 and the properties for the flow simulations are shown
in Table 6.1. The matrix permeability was set as $9.9 \times 10^{-11}$ m$^2$ and the fracture permeability was defined using Equation 6.7. Thus, the tracer could flow through both the fractures and the matrix, but the fracture permeability was considerably higher than the matrix permeability. Conductive tracer with 22 wt% NaCl concentration was injected at 10 kg/s at the injector and the three producers were modeled to deliver against a bottom hole pressure of $10^6$ Pa. The simulation time for the flow simulation was set as 100 days.

6.1.3 Electric Simulation

The electric fields for the fracture network library were calculated at different times using GPRS. The procedure for calculating electric fields using GPRS was described in Section 3.2.2. Equation 2.1 and Equations 3.23-3.25 were used to calculate the
resistivity distributions at different time steps based on the temperature and NaCl concentration of the fractures and the rock matrix. For Equation 2.1, $d$ was set as 0.62 and $e$ as 1.95 which corresponds to well-cemented sedimentary rocks with porosity 5-25% [56] and the following $B$ matrix [100] was used in Equations 3.23-3.25,

$$B = \begin{bmatrix}
3.470 & -6.650 & 2.633 \\
-59.23 & 198.1 & 64.8 \\
0.4551 & -0.2058 & 0.005799 \\
-0.346 \times 10^{-5} & 7.368 \times 10^{-5} & 6.741 \times 10^{-5} \\
-1.766 \times 10^{-6} & 8.787 \times 10^{-7} & -2.136 \times 10^{-7}
\end{bmatrix} \quad (6.8)$$

The main difference between the electric simulations described in this chapter and the simulations described in previous chapters is that here the matrix is assumed to be permeable so the electrical resistivity was calculated for all the elements in the reservoir according to each element’s porosity and tracer concentration.

For each resistivity distribution, the current was first set as 1 A at the injector and as -1 A at Producer 1 and the electric field calculated using the analog between Ohm’s law and Darcy’s law as described in Section 3.2.1. Then, the same procedure was repeated for all other well pairs. The properties for the electric simulation are shown in Table 6.1. The viscosity at the initial pressure and temperature conditions was $8.899 \times 10^{-4}$ Pa s, which is the viscosity used in Equation 3.22 to calculate the permeability corresponding to the resistivity of the field. The flow rate at the injection well was calculated using Equation 3.21 and then scaled as outlined in Table 6.4 to obtain sufficient digits for the electric results. In order to account for the scaling of the flow rates and permeability, the pressure results were multiplied by 10 to obtain the corresponding voltage results.
Table 6.4: Scaling of electric parameters for the input in GPRS for the fracture network library.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Multiplied by:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flow rates at wells</td>
<td>$10^{-3}$</td>
</tr>
<tr>
<td>Permeability</td>
<td>$10^{-4}$</td>
</tr>
<tr>
<td>Pressure results</td>
<td>10</td>
</tr>
</tbody>
</table>

6.1.4 Number of Fracture Networks Increased

The computer power available for this study allowed for 600 candidate fracture networks to be generated. In order to increase the number of distinctive fracture networks the mirror images of the networks were used as well. The location of the injector and producers is symmetrical about a vertical line in the middle of the reservoir as demonstrated in Figure 6.5. The electric potential difference between the injector and Producer 1 is the same as the electric potential difference between the injector and Producer 2 for the mirror image of the network (and vice versa). The same applies for electric potential between Producer 1 and Producer 3, and between Producer 2 and Producer 3. Other well pairs are unchanged. By using the mirror images of the networks, the number of distinctive fracture networks in the fracture network library was doubled without any additional simulations. Therefore, a total of 1200 different fracture networks could be used for the inverse analysis in this study.
6.2 Inversion

An inverse analysis was used in this study with the time history of the electric potential to estimate the connectivity of fractured reservoirs. In inverse modeling, the results of actual observations are used to infer the values of the parameters characterizing the system under investigation. In this case, the output parameters were the potential differences between wells as a function of time and the input parameter was the character of the corresponding fracture network. The objective function measured the difference between the model calculation (the calculated voltage difference between the wells) and the corresponding observed data measured at the reservoir, as illustrated in Figure 6.6. An optimization algorithm was used to find the network with the most similar characteristics by proposing new parameter sets that improved the match iteratively. A synthetic reservoir was used as the ‘true’ reservoir, and was compared to the library of 1200 fracture networks to find the best match. Due to the relatively small number of fracture networks, a grid
search algorithm could be used to compare the reservoir response to that of all the fracture networks in the library of networks. The best match was found using least squares, where the sum of the squared deviations between the electric curves for the true reservoir and the electric curves for the fracture networks was minimized. For every well pair in the reservoir, the following least squares criterion was calculated,

\[ Z_j = \sum_{i=1}^{n} [y_i - f_i]^2 \]  \hspace{1cm} (6.9)

where \( y_i \) is the electric potential difference between well pair \( j \) in the reservoir at time \( i \) and \( f_i \) is the corresponding electric potential for a fracture network in the library of networks. Then, the sum of \( Z_j \) for all well pairs was minimized to find the best match.
6.3 Fracture Characterization Indices

The fracture characterization indices described in Chapter 5 were considered for the inverse analysis to describe the important fracture characteristics of the reservoirs. The indices considered were the fracture density parameter, connectivity index, fractional connected area and the fractal dimension.

6.3.1 Fracture Density Parameter

The fracture density parameter (Section 5.1) describes the fracture density of a fracture network but does not take into account the spatial fractal distribution of
fractures. Watanabe and Takahashi [103] used the fracture density parameter to predict hydraulic properties in fractured reservoirs but assumed the fracture locations were distributed randomly. Due to the numerous studies demonstrating spatial fractal distributions in reservoirs [6, 36, 44, 64], the fracture networks in the library of networks in this study were modeled with varying spatial fractal dimensions. In order to take the spatial distribution into account, the fracture density parameter was not used for the inverse analysis in this study. The objective was to find a characterization index that would be representative of the fluid movement in the reservoir in order to predict thermal breakthrough. In reservoirs where spatial fractal distribution is assumed, some areas might have more fractures than others. Thus, thermal breakthrough would be different for wells located in these areas than for wells located in less fractured areas. The fracture density parameter is useful to capture the overall fracture density but not the fractal spatial distribution because it assumes the same density in the whole reservoir. The fractal length distribution was also assumed to be fractal but the fractal dimension of the length distribution was assumed to be the same for all networks. Thus, the proportionality coefficient $B$ was constant, calculated using Equation 6.5, instead of defining $B$ as the fracture density parameter and a random spatial distribution of fractures, as done in studies by Watanabe and Takahashi [103].

6.3.2 Connectivity Index

The connectivity index (Section 5.4) is useful for describing possible connections through fractures between two points and for quantifying fracture connectivity as described by Xu et al. [107]. However, similarly to the fracture density parameter,
the spatial distribution is not taken into account. One value is calculated for the connectivity index describing the probability of a connection between any two points in the field. For the connectivity index to represent the connectivity of the field successfully, the connectivity has to be similar for the whole field. For example, the spatial fracture distribution for a field with highly fractured areas as well as areas with no fractures would not be described sufficiently by a connectivity index. Thus, the connectivity index was not used for the inverse analysis in this study.

6.3.3 Fractional Connected Area and Fractal Dimension

The fractional connected area (Section 5.3) and the spatial fractal dimension (Section 5.2) take into account the spatial distribution of the fractures. These fracture characterization indices were found likely to describe the connectivity for reservoirs with both highly fractured areas as well as no fracture zones. Thus, sensitivity analyzes were performed to investigate whether there was a correlation between the electric potential difference between well pairs in the reservoir and these fracture characterization indices.

First, the effect of Fractional Connected Area (FCA) on the time-varying electric potential curves was studied. For each fracture network in the library of networks, the electric potential difference between the injector and Producer 1 was plotted. Then, the same procedure was repeated for all other well pairs. Figure 6.7 shows the electric potential curves and the Fractional Connected Area (FCA) represented by color for all well pairs. The electric potential difference between the injector and the other wells (Figure 6.7a-c) drop quickly in the beginning because conductive tracer flows through the area between these wells as soon as it is injected at the injector.
correlation between the FCA and the electric potential differences between the injector and Producer 1 (Figure 6.7a) is not clear because the electric potential depends a lot on whether fractures happen to be located between these wells or not. The same applies for the injector and Producer 2 (Figure 6.7b). However, a clear trend can be seen in the data for the well pair consisting of the injector and Producer 3, shown in Figure 6.7c. The electric curves for high FCA (in red) drop faster than electric curves for low FCA (in blue). High FCA corresponds to better connected reservoir with tracer traveling faster towards the producers, causing the electric potential to drop. This well pair covers almost the whole reservoir and therefore represents the connectivity of the reservoir better than the previous well pairs.

Similar trends can be seen between the other wells in the reservoir (Figure 6.7d-f), i.e. between Producers 1 and 3, Producers 2 and 3, and Producers 1 and 2. The time it takes for the tracer to reach the areas between these wells depends on the connectivity from the injector towards these areas. Thus, the electric differences depend not only on the fractures between the well pairs but also on the fractures forming paths from the injector towards these areas. In the inversion of the electric curves, all well pairs are used and the overall trend in the sensitivity analysis has shown a good correlation between the electric curves and Fractional Connected Area (FCA).

Next, the effect of the spatial fractal dimension $D$ on the electric curves was investigated. The electric potential differences between all well pairs were plotted with the spatial fractal dimension represented by color, shown in Figure 6.8. The correlation between the electric curves and the spatial fractal dimension is very similar to the correlation between the electric curves and the Fractional Connected Area (FCA). Figure 6.8c-f shows electric curves for reservoirs with a high fractal dimension
(red) dropping faster than electric curves for reservoirs with a low fractal dimension (blue). A high spatial fractal dimension corresponds to a better connected field because fractures are distributed over a larger part of the reservoir.

The sensitivity analyzes showed good correlation between the time-history of the electric potential curves and both the fractional connected area as well as the spatial fractal dimension. These fracture characterization indices were chosen for the inverse analysis to describe the character of the fractured reservoirs in the library of networks.
Figure 6.7: Fractional connected area (color) with electric curves between a) injector and Producer 1, b) injector and Producer 2, c) injector and Producer 3, d) Producer 1 and Producer 3, e) Producer 2 and Producer 3, and f) Producer 1 and Producer 2.
Figure 6.8: Spatial fractal dimension $D$ (color) with electric curves between a) injector and Producer 1, b) injector and Producer 2, c) injector and Producer 3, d) Producer 1 and Producer 3, e) Producer 2 and Producer 3, and f) Producer 1 and Producer 2.
6.4 Summary

This chapter described the process of characterizing fracture connectivity using time-lapse electric potential data with conductive fluid injection. A library of discrete fracture networks with varying spatial fractal dimensions was generated and GPRS used to simulate the flow of a conductive tracer through the reservoirs. Then, GPRS was used to solve the electric field at each time step while the fluid flows from the injector towards the producers. The time-history of the electric potential depends on the connectivity of the network because the electric potential difference between wells drops as conductive fluid decreases the resistivity between the wells.

An inverse analysis was described for finding the network that best represents the fractured reservoir by comparing time-lapse electric potential data. The fractional connected area and spatial fractal dimension were chosen as fracture characterization indices to describe the character of the fracture networks in this study. These indices capture the spatial distribution of fractures and sensitivity analyses showed correlations between the indices and the time-history of the electric fields.
Chapter 7

Fracture Characterization

This chapter summarizes the results of using the inverse method described in Chapter 6 to characterize fractured geothermal reservoirs. One of the fracture networks in the library of networks was chosen as a hypothetical ‘true’ geothermal reservoir and the inverse analysis was used with the time histories of the electric potential to estimate the connectivity of the reservoir. The procedure was repeated for a number of fracture networks in the library of networks.

The connectivity was quantified by the Fractional Connected Area (FCA) (Section 5.3) and the spatial fractal dimension (Section 5.2). The feasibility of using either one of these fracture characterization indices to characterize fracture networks is discussed in this chapter. In addition, the location of the connected areas was compared visually between the best matches and the true reservoirs. Estimating the FCA or spatial fractal dimension can give valuable information about the flow behavior in the reservoir but it is also important to know where in the reservoir the fractures are located in order to predict the future production accurately.
For comparison, the inverse analysis was also used with the tracer return curves at the producers instead of the time-lapse electric data. A sensitivity analysis was performed where the correlation between the tracer return curves and the Fractional Connected Area (FCA) as well as between the tracer return curves and the spatial fractal dimension was investigated. The goal was to study how the performance results of the electric method compared to using just the simple tracer return curves to predict the connectivity of geothermal reservoirs.

7.1 Inversion of Electric Potential Data

For the inverse method described in Chapter 6, one of the fracture networks in the library of 1200 networks was chosen as the ‘true’ geothermal reservoir. Then, the inverse analysis was used to find the best match for the chosen reservoir by comparing time-lapse electric potential data between all well pairs. The inverse method was performed for 70 days of tracer injection. Grid search algorithm was used to find the best match by minimizing the least squares criterion explained in Section 6.2. The procedure was repeated for other networks, of which two are discussed in detail in this section. The results for other networks are summarized in Section 7.3.

7.1.1 Reservoir 1

The reservoir chosen as the true reservoir for the first case, referred to as ‘Reservoir 1’, is shown in Figure 7.1. The Fractional Connected Area (FCA) of Reservoir 1 is 27% and the spatial fractal dimension is $D = 1.2$. Other reservoir properties and the simulation properties for the tracer and electric simulations are listed in Table 6.1.
The connected area of the reservoir is shown in Figure 7.2a and the electric potential curves between all well pairs are shown in Figure 7.2b. The electric potential curves calculated between the injector and Producer 1, injector and Producer 2, and injector and Producer 3, drop once tracer is injected into the reservoir due to the low resistivity of the injected fluid. The fluid reaches the area between the other well pairs later so the corresponding electric potential curves decrease slower at the start. Then, the curve between the injector and Producer 1 drops relatively quickly and correctly indicates a good connection towards Producer 1.

Another interesting observation is that the curve between Producer 2 and Producer 3 drops relatively slowly despite a good connected area between these wells. That can be explained by looking at the tracer distribution shown in Figure
Figure 7.2: a) Reservoir 1 with connected area shown in red, b) electric potential difference between wells for Reservoir 1, c) the best match for Reservoir 1 when matching electric potential curves, and d) electric potential difference between wells for the best match.

7.3. Substantial amount of tracer flows towards Producer 1 because of the well connected area between the injector and Producer 1, and the tracer travels slower towards Producer 2 because there are no fractures in that area. After 25 days (Figure 7.3a), the tracer has reached areas between all well pairs, but very little tracer has reached the area between Producer 2 and Producer 3, resulting in a
slower drop in electric potential difference between these wells. After 47 days (Figure 7.3b), the electric curves show similar electric potential difference between Producer 1 and Producer 3, and between Producer 2 and Producer 3. At that point, a considerable amount of tracer has reached the fractures leading towards the area between Producer 2 and 3.

![tracer distribution](image)

Figure 7.3: Tracer distribution \(\frac{kg_{tr}}{kg_{tot}}\) for Reservoir 1 after a) 25 days b) 47 days.

The simple tracer return curves at the producers were examined as well, as shown in Figure 7.4. The tracer return curves also indicate a good connection towards Producer 1, with tracer in Producer 1 increasing after about 4 days. A poor connection is indicated towards Producer 2 with no tracer in Producer 2 until after about 16 days. The tracer reaches Producer 3 sooner than Producer 2, or after 12 days, because of the fractures located from the middle of the reservoir towards the lower right corner in Figure 7.2a.

The inverse analysis described in Chapter 6 was used to find the best match for Reservoir 1 in the library of 1200 fracture networks by comparing time-lapse
electric potential data between all well pairs for 70 days of tracer injection. The chosen network that gave the best match is shown in Figure 7.2c and the electric potential curves for the network are shown in Figure 7.2d. The curves for the electric potential show very similar behavior to the curves for the true reservoir (Figure 7.2b). The electric potential curve between the injector and Producer 1 for the best match drops quickly because of a connected area located between these wells. There is no connected area between the injector and Producer 2 so the tracer flows faster towards Producer 1 than towards Producer 2. Consequently, the electric potential curve between Producer 2 and Producer 3 drops slower because the tracer reaches the area between Producer 2 and Producer 3 later. Despite the electric potential curves matching very well for the true reservoir and the best match, the tracer return curves shown in Figure 7.5 for the best match show somewhat different behavior than the tracer return curves for Reservoir 1 (Figure 7.4).
Figure 7.5: Tracer return curves for the best match for Reservoir 1 when using tracer return curves.

The Fractional Connected Area (FCA) of the network in Figure 7.2c was compared to the FCA of Reservoir 1. The results were FCA = 27% for Reservoir 1 as well as for the best match. Thus, FCA matches for these two networks, indicating that FCA can be predicted in this example using this electric potential method. Similarly, the spatial fractal dimensions of the two reservoirs match well, $D = 1.2$ for Reservoir 1 and $D = 1.1$ for the best match. The spatial fractal dimension (described in Section 6.1.1) is used to define the number of boxes chosen for fracture centers which is at ith iteration equal to $2^{D_i}$, but the number is rounded to the nearest integer. Thus, two very similar fracture networks can be generated despite a small difference in the spatial fractal dimensions for the two networks.

Another similarity that can be seen between the best match and Reservoir 1 is the location of the connected areas. In both cases the connected fractures are located similarly in the upper left corners of Figure 7.2a and Figure 7.2c and the connected
area reaching from the middle of the reservoir towards the area between Producer 2 and Producer 3 was also predicted correctly. However, the best match in Figure 7.2c also has a connected area in the lower right corner of the figure, which is different from the true reservoir. The tracer travels from the injector towards the producer and might never reach the corners of the reservoir. Even if the tracer does reach these areas, it will not affect the electric potential between the wells considerably if the shortest distance between the wells has already been saturated with tracer. Thus, the electric potential gives very limited information about these areas.

Overall, the connected areas in Figure 7.2a and Figure 7.2c are similar, and the drops in electric potential between the well pairs correspond to the locations of the connected areas. These results indicate a good possibility of using electric potential calculations while injecting a conductive tracer into reservoirs to predict the spatial fractal dimension, the fractional connected area, and the location of the connected areas.

7.1.2 Reservoir 2

A second case was studied and the fracture network chosen as the ‘true’ reservoir is shown in Figure 7.6. The reservoir is referred to as ‘Reservoir 2’. The reservoir and simulation properties (listed in Table 6.1) are the same as for the previous networks, and all networks in the fracture network library. The connected area of the reservoir is shown in Figure 7.7a and the electric potential curves between all well pairs are shown in Figure 7.7b. The spatial fractal dimension of the reservoir is $D = 1.2$ and the Fractional Connected Area (FCA) is $18\%$. 
The electric potential difference between the injector and Producer 1 drops considerably faster than that between other well pairs due to the connected area between the injector and Producer 1. After the conductive tracer reaches Producer 1, the tracer travels towards Producer 3 through the fractured area in the lower left corner of the reservoir. The tracer travels, however, relatively slowly towards Producer 2 because there are no fractures in that area. The tracer return curves at the producers, shown in Figure 7.8, also indicate a considerably better connection towards Producer 1 than towards the other producers. The tracer reaches Producer 1 after 1 day but reaches Producer 2 after 26 days and Producer 3 after 28 days.

![Figure 7.6: Reservoir 2 (fractures shown in red).](image)

The inverse analysis compared the time histories of the electric potential difference between well pairs for Reservoir 2 to the library of fracture networks to find the
best match. The network that gave the best match is shown in Figure 7.7c and the electric potential curves are shown in Figure 7.7d. The curves for the electric potential show a very similar behavior to the curves for Reservoir 2 (Figure 7.7a). The Fractional Connected Area (FCA) of the best match is FCA = 25% compared to FCA = 18% for Reservoir 2. Thus, FCA is a bit higher for the best match. The
difference in Fractional Connected Area (FCA) can be explained by examining the difference between the fracture networks. In Reservoir 2, fractures are located close to the injector and leading towards Producer 1, but do not intersect any of the fractures in the connected area. These few fractures contribute to the flow but do not increase the size of the connected area. The electric potential difference between the injector and Producer 1 in Reservoir 2 drop faster due to these fractures so the best match contains fractures in that area. Thus, the Fractional Connected Area (FCA) might not match perfectly between the reservoirs and their best matches. However, the best match represents the flow behavior in Reservoir 2 correctly, which is more important than matching FCA for using the best match to predict the production history of the reservoir.

The spatial fractal dimension of the best match was also examined. The spatial fractal dimension of the best match is $D = 1.4$ but the spatial fractal dimension of
Reservoir 2 is $D = 1.2$. Therefore, this case demonstrates that the spatial fractal dimension can also be somewhat different between the reservoir and the best match despite the flow behavior being similar. The larger fractal dimension for the best match can be explained by fractures located in the upper right corner of Figure 7.7c. These fractures increase the spatial fractal dimension of the reservoir but all the fractures are oriented perpendicular to the flow direction from the injector towards Producer 2 and therefore do not increase the flow rate of the tracer towards the producer.

Fractional Connected Area (FCA) and spatial fractal dimension can give valuable information about the connectivity and the fracture distribution in geothermal reservoirs. However, this case has shown that estimating FCA and spatial fractal dimension with very high precision is not important, but rather to obtain an idea of where the fractures contributing to the flow are located in order to better understand the flow system.

The locations of the connected areas for the best match and Reservoir 2 are similar. In both cases the connected fractures are located similarly between the injector and Producer 1, resulting in a drop in potential difference between these wells as conductive fluid is injected into the reservoir. The connected area in the lower left corner of Figure 7.7a is also predicted correctly, causing the tracer to travel from the upper connected area, along the left side of the reservoir, towards Producer 3. Therefore, the electric potential difference between Producer 1 and Producer 3 drops considerably faster than the electric potential difference between Producer 2 and Producer 3. Similarly to Case 1, the tracer return curves for the best match, shown in Figure 7.9, show somewhat different behavior than the tracer return curves
for Reservoir 2 (Figure 7.8). Thus, it was of interest to compare the performance results of using the electrical approach to those using only tracer return curves to predict connected areas.

![Figure 7.9: Tracer return curves for the best match for Reservoir 2 when using tracer return curves.](image)

### 7.2 Inversion of Tracer Return Data

The fractional connected area and spatial fractal dimension were predicted successfully using the electric potential approach. In this section, the electric method is compared to just using the tracer return curves at the producers. A sensitivity analysis was performed for the tracer return curves at the producers, as shown in Figure 7.10 with color representing Fractional Connected Area (FCA). The tracer return curves were plotted for all the fracture networks in the library of networks to study the effect of FCA on the tracer return curves in comparison to
the effects on the electric curves illustrated previously in Figure 6.7. There is no clear trend for the tracer return curves at Producer 1 and Producer 2. There are curves with high FCA (in red) and with low FCA (blue) showing similar behavior because some fractures can be located between the injector and these producers despite the FCA being low. The tracer return curves at Producer 3 are more affected by the fractures in the whole reservoir and a slight trend with red curves (high FCA) increasing faster than blue curves (low FCA) can be noted.

Figure 7.10: FCA (color) with tracer return curves at a) Producer 1, b) Producer 2, and c) Producer 3.
A sensitivity analysis was also performed for the spatial fractal dimension, shown in Figure 7.11. Similarly to the Fractional Connected Area (FCA), there is no trend in the spatial fractal dimension for the tracer return curves at Producer 1 and Producer 2. There is also not a clear trend in spatial fractal dimension for the tracer return curves at Producer 3. There are both red (high spatial fractal dimension) and blue (low spatial fractal dimension) curves increasing fast and also some red and blue curves increasing very slowly. These sensitivity analyses indicate that the correlation between the tracer return curves and the spatial fractal dimension or the FCA, is not as strong as for the electric potential curves, especially for the 70 days of simulation used in the inverse analysis. Thus, tracer return curves may not be sufficient to predict FCA and the spatial fractal dimension.

7.2.1 Reservoir 1

In order to compare the performance results of using electrical measurements instead of using only tracer return curves, the inverse analysis was performed again for Reservoir 1 (Figure 7.1). This time the objective function measured the difference between the model calculation of just the simple tracer return curves and the corresponding tracer return curves for the true reservoir for 70 days of tracer injection. The electric data were not used. The best match when comparing the tracer return curves using a grid-search algorithm as before, can be seen in Figure 7.12. The time histories of the electric potential difference between the wells do not match as well as when they were used to find the best match. However, in this case the tracer return curves shown in Figure 7.13 match better than before to the tracer return curves for Reservoir 1 (Figure 7.4).
The fractal dimension is the same as for the reservoir, $D = 1.1$, but the estimated Fractional Connected Area (FCA) for the network is 23%, thus a bit smaller than for the true reservoir where FCA = 27%. The FCA and spatial fractal dimension for Reservoir 1 and the best match using electric data and the best match using tracer data are summarized in Table 7.1. The best match for using the tracer data (Figure 7.12) does have a connected area between the injector and Producer 1, but instead of having a connected area from the middle of the figure towards the lower
CHAPTER 7. FRACTURE CHARACTERIZATION

Figure 7.12: a) The best match for Reservoir 1 when matching tracer return curves and b) the electric potential difference between wells.

Figure 7.13: Tracer return curves for the best match for Reservoir 1 when using tracer return curves.

right corner, this network has a connected area from the middle towards the lower left corner. Thus, tracer return curves indicate a connection in the middle towards Producer 3 but fail to determine the overall location of the largest connected area in
the reservoir, which was predicted correctly using the electric curves. Additionally, the connected area between the injector and Producer 1 is smaller than for Reservoir 1 because a relatively large fracture leading from the injector towards Producer 1 does not intersect any other fractures and does therefore not increase the connected area.

<table>
<thead>
<tr>
<th>Reservoir 1</th>
<th>Best match - electric</th>
<th>Best match - tracer</th>
</tr>
</thead>
<tbody>
<tr>
<td>FCA: 27%</td>
<td>27.0%</td>
<td>23%</td>
</tr>
<tr>
<td>D: 1.1</td>
<td>1.2</td>
<td>1.1</td>
</tr>
</tbody>
</table>

### 7.2.2 Reservoir 2

The tracer-only inverse analysis was also performed for Reservoir 2 (Figure 7.6). The best match when comparing the tracer return curves can be seen in Figure 7.14 and the tracer return curves are shown in Figure 7.15. For this case, FCA = 19% so FCA matches very well to Reservoir 2 where FCA = 18%. However, for the best match all of the connected area is located between the injector and Producer 1. Thus, tracer return curves indicate a good connection between the injector and Producer 1 but they do not predict the connected area between Producer 1 and Producer 3. Consequently, the spatial fractal dimension of the best match is smaller than for Reservoir 2 because of no fractures located in the lower left corner for the best match. The spatial fractal dimension for the best match is $D = 1.0$ but $D = 1.2$ for Reservoir 2. The Fractional Connected Area (FCA) and the spatial fractal dimension for Reservoir 2 and the best match using electric data, and the best match using tracer data are summarized in Table 7.2.
These examples have demonstrated that the location of the connected area is predicted better using the electric approach. The tracer concentration is only measured at the three producers so the tracer return curves give, for example,
Table 7.2: Comparison between using electric and tracer data to estimate FCA and spatial fractal dimension for Reservoir 2.

<table>
<thead>
<tr>
<th>Reservoir 2</th>
<th>Best match - electric</th>
<th>Best match - tracer</th>
</tr>
</thead>
<tbody>
<tr>
<td>FCA:</td>
<td>18%</td>
<td>25%</td>
</tr>
<tr>
<td>$D$</td>
<td>1.2</td>
<td>1.4</td>
</tr>
</tbody>
</table>

limited information about whether a connected area is located to the left or right of Producer 3. However, the tracer return curve at Producer 1 or Producer 2 will depend on the fractures in the area between the injector and Producer 1 or Producer 2. These fractures will also affect where the fluid enters the lower part of the reservoir. Thus, the tracer return curves might predict the Fractional Connected Area (FCA) and the spatial fractal dimension correctly but the distribution of fractures could still be quite different from the true reservoir.

### 7.3 Additional Examples

The previous two cases showed that the location of the connected area is predicted better using the electric approach than using just the simple tracer return curves. The same observation was also valid for other examples shown Figure 7.16. Reservoir 3 (shown in Figure 7.16a) has a spatial fractal dimension $D = 1.5$ and the best match using the electric curves are shown in Figure 7.16b. The spatial fractal dimension of the best match is $D = 1.3$. The connected area is predicted correctly between the injector and Producer 2, and between Producer 2 and Producer 3. Thus, for both networks the connected fractures form a path from the injector through the right side of the reservoir towards Producer 3. However, it was noted that the connected areas were not predicted as accurately as for lower spatial fractal dimensions. If the spatial
fractal dimension of the reservoir is high, more connected areas are present so the possible arrangements of connected areas increases. Therefore, a network perfectly matching the reservoir might not exist in the library of fracture networks. However, the overall connectivity is predicted correctly and in order to predict these areas with more precision, the number of fracture networks in the library of networks could be increased.

The best match for Reservoir 3 using the tracer return curves is shown in Figure 7.16c. The tracer return curves predict incorrectly some connected areas between the injector and Producer 1. The best match also has more fractures distributed over larger part of the reservoir and a higher spatial fractal dimension, $D = 1.8$. Therefore, the electric curves also predict the location of the connected areas better than the tracer return curves for this case. The fractures in the lower left corner of Reservoir 3 were not predicted with either method because the fractures have not been saturated with tracer after the 70 days of injection used for the inverse analysis, as shown in Figure 7.17.

The electric curves also predict the location of the connected areas correctly for Reservoir 4 and Reservoir 5 shown in Figure 7.16d and Figure 7.16g. The best match for Reservoir 4 does have an additional connected area between Producer 1 and Producer 3 because of fractures in Reservoir 4 contributing to the flow towards Producer 3 but not forming a connected area. For both Reservoir 4 and Reservoir 5 the tracer return curves do not predict the connected areas as accurately as the electric potential curves.

The inverse analysis was performed for 100 additional cases using first the electric curves and then the tracer return curves. The results for estimating Fractional
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Figure 7.16: a) Reservoir 3, b) best match for Reservoir 3 when using electric curves, c) best match for Reservoir 3 when using tracer curves, d) Reservoir 4, e) best match for Reservoir 4 when using electric curves, f) best match for Reservoir 4 when using tracer curves, g) Reservoir 5, h) best match for Reservoir 5 when using electric curves, and i) best match for Reservoir 5 when using tracer curves.

Connected Area (FCA) for 70 days of tracer injection are summarized in Figure 7.18. The difference between the FCA for the true reservoir and the predicted fracture network was within ±0.1 for 86% of the networks when using the electric curves.
and 79% of the networks when using tracer return curves. Thus, the electric curves predict FCA somewhat better. The fractal dimension was also predicted better using the electric curves. For 89% of the networks, the fractal dimension was predicted within ± 0.1 of the true fractal dimension. For the tracer return curves, the fractal dimension of 77% of the networks was predicted within ± 0.1 of the true fractal dimension. Therefore, the FCA and spatial fractal dimension are both estimated more accurately using the electric curves.

Previous examples demonstrated that the electric curves predicted the location of the connected areas better. However, the electric curves did not always predict the Fractional Connected Area (FCA) or the spatial fractal dimension correctly. Four scenarios occurred where the indices were not estimated accurately:

1. Fractures in the reservoir increased the size of a connected area but the fractures were oriented perpendicular to the flow direction. Thus, the fractures did not
increase the flow rate of the tracer towards the producers and the connected area did not occur in the predicted reservoir. The opposite can also occur, i.e. the predicted reservoir has fractures perpendicular to the flow direction that make the estimated connected area larger than for the true reservoir. The same applies for the spatial fractal dimension.

2. Fractures were oriented in the flow direction but did not intersect other fractures. The fractures contributed to the flow but did not increase the fractional connected area. Thus, the predicted network had higher FCA than the true reservoir (or vice versa).

3. The tracer did not reach the connected areas within 70 days of injection. The tracer travels from the injector towards the producers and might never reach
the corners of the reservoir. The tracer is more likely to not reach the areas in the lower corners of the reservoirs because it takes the tracer more time to reach these areas than closer to the injector at the top of the reservoir.

4. The electric curves for the true reservoir and the best match do not match well. In those cases, the number of fracture networks in the library of networks could be increased to increase the possibility of finding a good match.

7.4 Summary

In this chapter the possibility of using time-lapse electric data to predict the fracture connectivity of geothermal reservoirs was described. The spatial fractal dimension, Fractional Connected Area (FCA), and the location of the connected areas were estimated and the results were compared to using just the simple tracer return curves at the producers. The FCA and spatial fractal dimension were in most cases predicted correctly using the electric curves. However, in some cases the FCA was over- or underestimated due to fractures that increased the connected area but did not contribute to the flow, or fractures contributing to the flow but not intersecting other fractures. The spatial fractal dimension was also over- or underestimated if fractures not contributing to the flow occurred in the reservoir or the best match. Most importantly, the electric curves did predict the flow behavior in the reservoir correctly.

For some of the cases the tracer did not reach connected areas in the corners of the reservoir and the electric curves for the best match and the true reservoir also
did not always match well enough. In order to increase the chances of finding a good match, the number of fracture networks in the library of networks could be increased.

The tracer return curves did in some cases predict the Fractional Connected Area (FCA) and the spatial fractal dimension correctly but the prediction using electric curves was more accurate. The location of the connected areas were estimated well using the electric curves but the location of connected areas estimated using tracer return curves was often incorrect. The advantages of using the electric measurements include having more extensive data and being able to see the changes as the conductive fluid flows through the network even before the tracer would have reached the production wells.
Chapter 8

Estimation of Thermal Return

Fracture characterization is extremely important for understanding the fluid flow and thermal behavior in fractured geothermal reservoirs. The knowledge of the fluid flow patterns in the reservoir leads to the optimal designing of the injection and production strategies so that the thermal sweep efficiency of the injected water can be maximized while premature thermal interference at production wells is avoided. In this section of the research, the electric approach used in Chapter 7 to characterize fracture networks, was tested for predicting thermal behavior in geothermal reservoirs. For various cases, the temperatures at the producers for the ‘true’ reservoir was compared to the temperatures at the producers for the fracture network that gave the best match when using electric data in the inverse analysis. The objective was to investigate the possibility of using the best match to predict the thermal behavior in the reservoir.

The estimation of thermal behavior in the reservoir using the electric approach was compared to using either only the tracer return curves in the inverse analysis or the tracer and electric curves combined. In addition, the feasibility of using the electric approach for estimating the thermal behavior for different
injection/production schemes was investigated and compared to using just the tracer tests. Both methods were also tested and compared for a conductive tracer injection performed over a shorter period of time. In some cases, tracking the tracer movement quickly might be important to avoid negative impacts on nearby steam production.

8.1 Thermal Breakthrough

Steam or hot water flashed to steam by lowering its pressure is produced in geothermal reservoirs to drive steam turbines and generate electricity. Any water produced from the reservoir is normally reinjected into the reservoir to maintain reservoir fluid and pressure as well as to avoid thermal or chemical pollution that would result from disposing the water into surface waterways. The replacement of the reservoir fluid can increase the energy extraction efficiency but the reinjected fluid is colder than the reservoir. The drawback of reinjection in fractured reservoirs is that the reinjected water can flow prematurely through highly conductive fractures back into production wells before the fluid has heated up enough, thereby reducing the discharge enthalpy and the useful energy output. Thus, it is important to gain information about the fractures in the reservoir in order to predict thermal breakthrough time and develop the recovery strategy efficiently.

Chemical tracers have been used to investigate connectivity between wells to prevent premature thermal breakthrough [30, 31]. The chemical front of a tracer injected into the reservoir reaches the production wells faster than the thermal front because the injected fluid is heated as it passes through the reservoir. In a porous medium, large quantities of water could be heated by the water transferring in
a uniform widespread manner through the rock. A number of analytical models have been presented on heat transfer due to a purely convective flow in a porous medium [38, 65, 87]. In fractured geothermal reservoirs, the thermal breakthrough time would be shorter but the porous medium models could give information about the maximum possible thermal breakthrough time. The thermal behavior in fractured geothermal reservoirs is considerably different from that in a porous medium because the fluid in fractures is in contact with a much smaller volume of rock so the fluid cools the adjacent rock relatively quickly. Pruess and Bodvarsson [84] presented a model for flow in a linear vertical fracture. They established a relationship for the estimation of thermal breakthrough time from the tracer breakthrough time. However, the relationship is dependent on the fracture aperture which is likely to be unknown.

These studies indicate that the tracer return curves at the producers would be useful in the inverse analysis for estimating thermal return. In the electric approach, the electric potential difference between the wells gives not only information about when the tracer reaches the production wells and a high conductivity path is formed between the injector and the producer, but also information about where the tracer flows even before it has reached the producers. Thus, it was of interest to investigate the possibility of using the electric approach to predict the thermal behavior in geothermal reservoirs and compare the results to using only the tracer return curves.
8.2 Thermal Return Estimated Using Time-Lapse Electric Potential Data

Thermal return curves were simulated for the fracture networks studied in Chapter 7 to investigate the possibility of using electrical potential measurements to predict temperature declines in geothermal reservoirs. The initial temperature of the reservoir models was set as 200°C and the injected fluid was at 100°C. The simulation was run for 30 years which is the typical amortization period of a geothermal power plant. The fracture networks simulated in this study are smaller than most real geothermal reservoirs. Thus, the water was injected at a relatively slow rate, 1 kg/s, and the production wells were modeled to deliver against a bottom-hole pressure of $10^6$ Pa which usually resulted in a reservoir lifetime of 15-30 years. The reservoir and simulation parameters for the thermal simulation are listed in Table 8.1.

8.2.1 Reservoir 1

As an example, the connected area of Reservoir 1 is shown in Figure 8.1a and the thermal return curves for Reservoir 1 are shown in Figure 8.1b. The temperature in Producer 1 dropped relatively quickly because of the connected area between the injector and Producer 1. The fluid cools rapidly the small volume of rock it is in contact with when flowing through the fractures. Thus, the rock does not heat the colder injected water enough and the colder water is quickly produced at Producer 1. The curve for Producer 2 dropped slower than for Producer 1 because there is no connected area between the injector and Producer 2. Producer 3 is located further away from the injector so the temperature decline in Producer 3 was also slower than
Table 8.1: Reservoir and thermal simulation properties for the fracture network library.

<table>
<thead>
<tr>
<th>Reservoir</th>
<th>SI-units</th>
<th>Oil-field units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dimension</td>
<td>1000×1000×1 m³</td>
<td>3281×3281×3.281 ft³</td>
</tr>
<tr>
<td>Fractal dimension (spatial)</td>
<td>1.0-1.8</td>
<td>1.0-1.8</td>
</tr>
<tr>
<td>Fractal dimension (length)</td>
<td>2.4</td>
<td>2.4</td>
</tr>
<tr>
<td>Fracture orientations (mean)</td>
<td>45°, 135°</td>
<td>45°, 135°</td>
</tr>
<tr>
<td>Maximum fracture length</td>
<td>600 m</td>
<td>1968.5 ft</td>
</tr>
<tr>
<td>Fracture width</td>
<td>0.002×L⁰.⁴ m</td>
<td>0.006562×L⁰.⁴ ft</td>
</tr>
<tr>
<td>Fracture porosity</td>
<td>0.9</td>
<td>0.9</td>
</tr>
<tr>
<td>Matrix porosity</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>Initial temperature</td>
<td>200°C</td>
<td>851.67 R</td>
</tr>
</tbody>
</table>

| Grid                           |          |                 |
| Max. fracture element size     | 305 m    | 1000 ft         |
| Minimum angle                  | 25°      | 25°             |

| Thermal simulation             |          |                 |
| Matrix permeability            | 9.869×10⁻¹¹ m² | 1×10⁵ md       |
| Fracture permeability          | w²/12    | u[m]²/12×1.0133×10¹⁵ md |
| Flow rate at injector          | 1 kg/s   | 543.43 STB/day  |
| BHP at producer                | 10⁶ Pa   | 145.0377 psi    |
| Product. index at producer     | 4×10⁻¹² m³ | 13123.36 md-ft |
| Simulation time                | 9.47×10⁶s | 10950 days      |
| Upper limit for time steps     | 8.64×10⁵ s | 10 days         |
| Lower limit for time steps     | 0.864 s  | 1×10⁻⁵ days     |

for Producer 1. However, despite Producer 3 being located further away from the injector, the thermal behavior is similar to Producer 2 because of the connected area between the injector and Producer 3 causing the temperature to decline faster than if there were no fractures.

After 15 years of production the temperature in Producer 1 had gone down to 121°C. Therefore, the production rate in Producer 1 would need to be decreased to prevent premature thermal breakthrough caused by the connected area between the
injection and Producer 1. In Producer 2, the temperature was at 155°C after 15 years and it was at 152°C in Producer 3.

The best match for Reservoir 1 that was determined in Section 7.1.1 using electric measurements is shown in Figure 8.1c and the corresponding thermal curves are shown in Figure 8.1d. Similarly to Reservoir 1, the temperature declined quickly in Producer 1 because of a connected area between the injector and Producer 1. The temperatures at the producers after 15 years of production are summarized in Table 8.2. The temperature in Producer 1 was at 114°C which is just a bit lower than for Reservoir 1 which was at 121°C after 15 years. The thermal return curves for Producer 2 and Producer 3 also showed similar behavior to the thermal return curves for Reservoir 1. The temperature in Producer 2 was at 152°C after 15 years of production which is very close to the temperature at Producer 2 in Reservoir 1 which was at 155°C. At the same time the temperature in Producer 3 was at 148°C while it was at 152°C for Reservoir 1. Thus, the thermal return in Reservoir 1 was predicted relatively well using the time-lapse electric data.

<table>
<thead>
<tr>
<th>Reservoir 1</th>
<th>Best match - electric</th>
</tr>
</thead>
<tbody>
<tr>
<td>Producer 1:</td>
<td>121°C</td>
</tr>
<tr>
<td>Producer 2:</td>
<td>155°C</td>
</tr>
<tr>
<td>Producer 3:</td>
<td>152°C</td>
</tr>
</tbody>
</table>

8.2.2 Reservoir 2

As a second example, Reservoir 2 is shown in Figure 8.2a and the corresponding thermal return curves are shown in Figure 8.2b. The temperature decreased fastest in Producer 1 because of well connected fractures located between the injector and
Figure 8.1: a) Reservoir 1, b) thermal return curves for Reservoir 1, c) best match for Reservoir 1 when using electric curves, and d) thermal return curves for the best match.

Produc er 1. The area between the injector and Producer 2 does not have any fractures so the temperature decreased slower in Producer 2. Producer 3 is located further away from the injector and there are no fractures in the middle of the reservoir that would cause the fluid to flow straight from the injector towards Producer 3, so the fluid flows through the area between Producer 2 and Producer 3 which caused the temperature in Producer 3 to decrease slower than for the other producers. The temperature in
Producer 1 was at $107^\circ C$ after 15 years of production, the temperature in Producer 2 was at $156^\circ C$, and the temperature in Producer 3 was at $192^\circ C$.

The best match for Reservoir 2 when using the time-lapse electric data (Section 7.1.2) is shown in Figure 8.2c and the corresponding thermal return curves are shown in Figure 8.2d. The thermal curves for the best match are similar to the thermal curves for Reservoir 2. In Producer 1 the temperature dropped somewhat faster for the best match than Reservoir 1 while in Producer 3 the temperature dropped a bit slower for the best match. That can be explained by the connected area between the injector and Producer 1 being larger for the best match than Reservoir 1, while the connected area between Producer 1 and Producer 3 is somewhat smaller for the best match.

After 15 years of production for the best match, the temperature in Producer 1 was at $100^\circ C$ compared to $107^\circ C$ for Reservoir 2, and the temperature in Producer 2 was at $158^\circ C$ compared to $156^\circ C$ for Reservoir 2, as summarized in Table 8.3. The temperature in Producer 3 was the same for the best match and Reservoir 2, $192^\circ C$. Thus, the best matches for Reservoir 1 and Reservoir 2 have shown that the electric curves can be used to predict the temperature in these reservoirs with relatively good accuracy.

<table>
<thead>
<tr>
<th>Producer</th>
<th>Reservoir 2</th>
<th>Best match - electric</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>107°C</td>
<td>100°C</td>
</tr>
<tr>
<td>2</td>
<td>156°C</td>
<td>158°C</td>
</tr>
<tr>
<td>3</td>
<td>192°C</td>
<td>192°C</td>
</tr>
</tbody>
</table>
Figure 8.2: a) Reservoir 2, b) thermal return curves for Reservoir 2, c) best match for Reservoir 2 when using electric curves, and d) thermal return curves for the best match.

8.3 Thermal Return Estimated Using Tracer Return Data

Tracer tests have been useful for predicting thermal breakthrough in geothermal reservoirs, so it was of interest to compare the electric approach to using only the
tracer return curves at the producers to predict the thermal behavior in the reservoirs. The thermal behavior was examined for the best matches when using tracer return curves in the inverse analysis for Reservoir 1 and Reservoir 2, previously determined in Section 7.2.

8.3.1 Reservoir 1

The best match for Reservoir 1 when comparing tracer return curves (Section 7.2.1) is shown in Figure 8.3a and the corresponding thermal return curves are shown in Figure 8.3b. The thermal curves are very similar to the thermal curves for Reservoir 1 (Figure 8.1b). The temperature in Producer 1 declines quickly due to a fractured area and a long fracture leading from the injector towards Producer 1. The temperature declines slower for Producer 2 because of no fractures in that area. It is also important to note that the temperature in Producer 3 is very similar for the best match and Reservoir 1 despite the best match not representing the connected areas in Reservoir 1 correctly. The best match (Figure 8.3a) has a connected area from the middle of the reservoir towards the left side while Reservoir 1 (Figure 8.1a) has a connected area from the middle towards the right side of the reservoir. The electric curves did predict this area correctly but for the thermal behavior in this case the exact location of this connected area is not that important. The temperature in Producer 3 will not depend on whether the fluid is flowing from the left or the right side of the reservoir.

The temperatures at the producers after 15 years of production for Reservoir 1, for the best match using electric curves, and for the best match using only tracer return curves are shown in Table 8.4. For this case, both electric curves and tracer
curves predict the temperature well. The temperature values predicted using the tracer return curves are somewhat closer to the temperature values for Reservoir 1.

![Diagram showing tracer return curves and thermal return at producers.]

Figure 8.3: a) The best match for Reservoir 1 when matching tracer return curves and b) the thermal return at the producers.

<table>
<thead>
<tr>
<th>Reservoir 1</th>
<th>Best match - electric</th>
<th>Best match - tracer</th>
</tr>
</thead>
<tbody>
<tr>
<td>Producer 1:</td>
<td>121°C</td>
<td>114°C</td>
</tr>
<tr>
<td>Producer 2:</td>
<td>155°C</td>
<td>152°C</td>
</tr>
<tr>
<td>Producer 3:</td>
<td>152°C</td>
<td>148°C</td>
</tr>
</tbody>
</table>

8.3.2 Reservoir 2

The thermal return was also predicted for Reservoir 2 using the tracer return curves. The best match for Reservoir 2 (Section 7.2.2) and the corresponding thermal return curves at the producers are shown in Figure 8.4. The best match for Reservoir 2 does not have a connected area in the lower left corner of the reservoir like both Reservoir
2 and the best match using electric curves do. A connected area is located closer to the middle of the reservoir causing the tracer to flow faster towards Producer 3. Thus, despite the fluid not flowing from Producer 3 through the left side of the reservoir, the thermal behavior in Producer 3 for the best match is very similar to the thermal behavior in Producer 3 for Reservoir 2.

The temperatures after 15 years of production for Reservoir 2 are compared in Table 8.5. Both the electric data and the tracer return curves predict the temperature well.

![Figure 8.4: The best match for Reservoir 2 when matching tracer return curves.](image)

<table>
<thead>
<tr>
<th></th>
<th>Reservoir 2</th>
<th>Best match - electric</th>
<th>Best match - tracer</th>
</tr>
</thead>
<tbody>
<tr>
<td>Producer 1:</td>
<td>107°C</td>
<td>100°C</td>
<td>103°C</td>
</tr>
<tr>
<td>Producer 2:</td>
<td>156°C</td>
<td>158°C</td>
<td>156°C</td>
</tr>
<tr>
<td>Producer 3:</td>
<td>192°C</td>
<td>192°C</td>
<td>187°C</td>
</tr>
</tbody>
</table>
8.4 Additional Examples

The thermal behavior was also studied for the other reservoirs chosen previously in Section 7.3; Reservoir 3, Reservoir 4, and Reservoir 5. Figure 8.5 shows the thermal return curves for Reservoir 3, the best match using electric data, and the best match using only tracer return curves. The temperature in Producer 1 is predicted well using the electric data. The temperature in Producer 1 for the best match using the tracer return curves shows a different behavior than for Reservoir 3 because the best match has more fractures between the injector and Producer 3 than Reservoir 3 does. However, the tracer return data predicts the temperature decline in Producer 2 and Producer 3 better than the electric data does. The best match for the electric data has fewer fractures than Reservoir 3 so the temperature in Producer 3 declines slower than for Reservoir 3. As mentioned in Section 7.3, it is harder to find a good match for reservoirs with a lot of connected areas because there are more possible arrangements of the connected areas. There was no fracture network in the library of fractures that matched Reservoir 3 well, and therefore the thermal prediction is a little off. In order to increase the possibility of finding a good match in the library of networks, the number of networks in the library could be increased.

The thermal return curves for Reservoir 4 and Reservoir 5 as well as the predicted thermal behavior for these reservoirs are shown in Figure 8.6 and Figure 8.7. For Reservoir 4, the electric measurements predict the temperature somewhat better than the tracer return curves. In Reservoir 5, the temperature in Producer 1 and Producer 3 is predicted better using the electric curves but the temperature in Producer 2 is predicted better using only the tracer return.
In addition, 50 other cases were studied. For these cases, Figure 8.8 shows a comparison of the estimated time at which the temperature goes below 140°C in Producer 1 and Producer 2 for the electric approach as well as for the tracer approach where only the tracer return curves are used. As mentioned previously, Producer 3 is located further away from the injector than Producer 1 and Producer 2, so in some cases the temperature does not drop below 140°C within a simulation time of 30 years. Thus, the time at which the temperature in Producer 3 drops below 180°C was studied. The coefficients of determination were also calculated, shown in Table 8.7, to measure how well the times for the reservoirs were replicated by the estimated fracture networks. The coefficient of determination, $R^2$, is defined as,

$$R^2 = 1 - \frac{SS_{err}}{SS_{tot}}$$  \hspace{1cm} (8.1)

where $SS_{err}$ is the residual sum of squares,

$$SS_{err} = \sum_i (y_i - \bar{y})^2$$  \hspace{1cm} (8.2)

and $SS_{tot}$ is the total sum of squares,

$$SS_{tot} = \sum_i (y_i - f_i)^2$$  \hspace{1cm} (8.3)

In Equations 8.2 and 8.3, $y_i$ is the data (e.g. time) for reservoir $i$, $\bar{y}$ is the mean of the reservoir data for all reservoirs, and $f_i$ is the data for the best match of reservoir $i$.

The coefficient of determination is relatively good when using the electric curves to find the best match as well as when using only the tracer return curves. The tracer
approach gives somewhat better estimation than the electric approach. The coefficient of determination for Producer 3 is lower than for the other producers because the producer is located further away from the injector. Thus, the time it takes for the temperature to drop below 180°C depends on the fracture characteristics of a larger part of the reservoir.

Table 8.6: Coefficients of determination for estimating the time at which the temperature goes below 140°C in Producer 1 and Producer 2, and below 180°C in Producer 3.

<table>
<thead>
<tr>
<th></th>
<th>Electric approach</th>
<th>Tracer approach</th>
</tr>
</thead>
<tbody>
<tr>
<td>R² for Producer 1:</td>
<td>0.87</td>
<td>0.94</td>
</tr>
<tr>
<td>R² for Producer 2:</td>
<td>0.90</td>
<td>0.94</td>
</tr>
<tr>
<td>R² for Producer 3:</td>
<td>0.71</td>
<td>0.78</td>
</tr>
</tbody>
</table>

For the 50 cases, the temperature after 15 years of production was also examined in Producer 1 and Producer 2. The results are shown in Figure 8.9. The temperature in Producer 3 was examined after 30 years of production because the temperature after 15 years was often still very high because of Producer 3 being located further away from the injector than the other producers. The coefficients of determination were compared for the two different approaches, shown in Table 8.7. The electric approach gives a better estimation of the temperature than the tracer approach for Producer 2. There is, however, very little difference between the electric approach and the tracer approach for Producer 2 and there is no difference for Producer 1. Both methods estimate the temperature relatively well. The temperature in Producer 3 is estimated better using only the tracer return curves but it is not estimated as accurately as for the other producers because it is located further away from the injector.
Table 8.7: Coefficients of determination for estimating the temperature after 15 years in Producer 1 and Producer 2, and after 30 years in Producer 3.

<table>
<thead>
<tr>
<th></th>
<th>Electric approach</th>
<th>Tracer approach</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R^2$ for Producer 1:</td>
<td>0.85</td>
<td>0.85</td>
</tr>
<tr>
<td>$R^2$ for Producer 2:</td>
<td>0.89</td>
<td>0.88</td>
</tr>
<tr>
<td>$R^2$ for Producer 3:</td>
<td>0.07</td>
<td>0.29</td>
</tr>
</tbody>
</table>

The electric approach and the tracer approach estimated the thermal behavior in most cases relatively well. In some cases, the electric curves predicted the temperature decline better than the tracer return curves. The electric data measures when the conductive tracer reaches the production wells and a highly conductive path has been formed from the injector towards the producer. The electric data also measures where the tracer flows before it has reached the production wells. However, despite the electric measurement providing more extensive data, the tracer return curves predicted the temperatures better in some cases. That is likely due to the limited number of fracture networks in the library of networks. While the tracer measurements give information about when the tracer has reached the production wells, which has in previous studies been found to be directly correlated with the thermal breakthrough time [84], the electric measurements also depend on where in the reservoir the tracer is flowing. The temperature is only measured at the producers, so the measured temperature does not depend on whether the fluid is flowing through fractures on the left or right side of the producer. Thus, if a network does not exist that matches well for both the tracer concentration at the producer and the overall location of connected areas in the reservoir, the electric curves will find a match were both the time the tracer reaches the production well and the overall location of connected areas is matched.
to some extent. Another network might exist where the time the tracer reaches the production well matches better to the true reservoir, which would be the best match if only the tracer return curves were used. However, for that case, the location of the fractures might be off. Therefore, the tracer approach might predict the thermal breakthrough time better for the injection scheme used for the tracer tests, but the overall fracture distribution is predicted better using the electric approach. The importance of predicting the location of the fractured areas is discussed in more detail in the following sections.
Figure 8.5: a) Reservoir 3, b) thermal return for Reservoir 3, c) the best match for Reservoir 3 when using electric curves, d) thermal return curves for the best match when using electric curves, e) the best match for Reservoir 3 when using tracer curves, f) thermal return curves for the best match when using tracer curves.
Figure 8.6: a) Reservoir 4, b) thermal return for Reservoir 4, c) the best match for Reservoir 4 when using electric curves, d) thermal return curves for the best match when using electric curves, e) the best match for Reservoir 4 when using tracer curves, f) thermal return curves for the best match when using tracer curves.
Figure 8.7: a) Reservoir 5, b) thermal return for Reservoir 5, c) the best match for Reservoir 5 when using electric curves, d) thermal return curves for the best match when using electric curves, e) the best match for Reservoir 5 when using tracer curves, f) thermal return curves for the best match when using tracer curves.
Figure 8.8: The time [days] at when the temperature goes below 140°C in a) Producer 1, b) Producer 2, and below 180°C in c) Producer 3.
Figure 8.9: The temperature [°C] after 15 years in a) Producer 1, b) Producer 2, and after 30 years in c) Producer 3.
8.5 Thermal Return Estimated Using Time-Lapse Electric and Tracer Data Combined

The previous section demonstrated how electric potential between wells could be used to estimate thermal behavior in geothermal reservoirs and the results were similar to the results obtained from the tracer return curves. The possibility of using the electric curves and the tracer return curves combined in an inverse analysis was also investigated. That way, more importance is given to the tracer breakthrough time than when using only the electric data because the tracer breakthrough time affects both the tracer and the electric measurements. The electric data ensured that the location of the connected areas were matched as well. In order to normalize the curves, the electric curves were divided by the maximum electric potential difference value for all the well pairs in the reservoir under study, and all the tracer curves were divided by the injected tracer concentration. Using 50 examples, Figure 8.10 demonstrates the estimation of time at which the temperature in Producer 1 and Producer 2 goes below 140°C, and the temperature in Producer 3 goes below 180°C. Table 8.8 shows the corresponding coefficients of determination. The results show that the time is predicted well using the electric and tracer curves combined, and is predicted somewhat better than when using only the tracer curves or only the electric curves for Producer 2 and Producer 3.

Figure 8.11 shows the estimated temperature in Producer 1 and Producer 2 after 15 years of production, and the temperature in Producer 3 after 30 years of production when using the electric and tracer data combined in the inverse analysis. The corresponding coefficients of determination are shown in Table 8.9. Similarly
Table 8.8: Coefficients of determination for estimating the time at which the temperature goes below 140°C in Producer 1 and Producer 2, and below 180°C in Producer 3.

<table>
<thead>
<tr>
<th></th>
<th>Electric approach</th>
<th>Tracer approach</th>
<th>Electric and tracer</th>
</tr>
</thead>
<tbody>
<tr>
<td>R² for Producer 1:</td>
<td>0.87</td>
<td>0.94</td>
<td>0.91</td>
</tr>
<tr>
<td>R² for Producer 2:</td>
<td>0.90</td>
<td>0.94</td>
<td>0.95</td>
</tr>
<tr>
<td>R² for Producer 3:</td>
<td>0.71</td>
<td>0.78</td>
<td>0.81</td>
</tr>
</tbody>
</table>

as before, the results for using only the tracer curves or only the electric curves are similar to using the tracer and electric curves combined. Overall, all three methods estimate the thermal behavior relatively accurately for Producer 1 and Producer 2 but less accurately for Producer 3.

Table 8.9: Coefficients of determination for estimating the temperature after 15 years in Producer 1 and Producer 2, and after 30 years in Producer 3.

<table>
<thead>
<tr>
<th></th>
<th>Electric approach</th>
<th>Tracer approach</th>
<th>Electric and tracer</th>
</tr>
</thead>
<tbody>
<tr>
<td>R² for Producer 1:</td>
<td>0.85</td>
<td>0.85</td>
<td>0.82</td>
</tr>
<tr>
<td>R² for Producer 2:</td>
<td>0.89</td>
<td>0.88</td>
<td>0.91</td>
</tr>
<tr>
<td>R² for Producer 3:</td>
<td>0.07</td>
<td>0.29</td>
<td>0.13</td>
</tr>
</tbody>
</table>
Figure 8.10: The time [days] at when the temperature goes below 140°C in a) Producer 1, b) Producer 2, and below 180°C in c) Producer 3. 50 examples were considered.
Figure 8.11: The temperature [°C] after 15 years in a) Producer 1, b) Producer 2, and after 30 years in c) Producer 3. 50 examples were considered.
8.6 Advantages of Using Electric Data

The thermal return curves shown in this chapter have demonstrated that there is usually not much difference between the estimated thermal behavior using electric data and that estimated using only the tracer data. In some cases, the electric curves estimate the temperature somewhat better but in more cases the tracer return curves estimate the temperature better. However, there are some advantages of using the electric data instead of only the tracer return curves. Chapter 7 demonstrated that the location of the connected areas was better predicted using the electric curves. Thus, despite the tracer curves being able to predict thermal return in the direction of flow used for the tracer tests, the overall location of fractures is estimated better using the electric curves. If the well pattern is changed, the fluid flow direction in the reservoir will be different and the location of the fractures may be important. For example, if the fluid is injected at Producer 3 and produced at the injector, it will matter whether the fractures in the lower part of the reservoir are located to the right or the left of Producer 3. Figure 8.12 shows an example of a fracture network where the location of the injector and Producer 3 has been switched.

For 30 reservoirs, the thermal behavior was investigated for this different layout of wells, i.e. the location of the injector and Producer 3 was switched. Figure 8.13 shows the estimation of the time at which the temperature goes below 190°C in the producers. The results show that the time is not estimated accurately for Producer 1 and Producer 2. The tracer was injected previously at the injector and might not have reached the lower corners of the reservoirs, but these corners might affect the thermal return when the location of Producer 3 is different. The results also show that the electric curves predict the time better than the tracer return curves. That observation
Figure 8.12: An example of a fracture network with a different well layout.

is also confirmed by looking at the coefficient of determination for Producer 3, shown in Table 8.10. The coefficient of determination is considerably higher when the electric approach is used. The tracer curves can predict the temperature of the fluid flowing the exact same path as the tracer but the electric measurements characterize the fractures in the whole reservoirs better than the tracer curves. Thus, if the injection scheme is changed to a different well pattern, the electric curves will estimate the thermal behavior better.

Table 8.10: Coefficient of determination for estimating the time at which the temperature goes below 190°C in Producer 3.

<table>
<thead>
<tr>
<th></th>
<th>Electric approach</th>
<th>Tracer approach</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R^2$ for Producer 3</td>
<td>0.79</td>
<td>0.23</td>
</tr>
</tbody>
</table>

Another advantage of using the electric curves instead of the tracer curves is that the electric measurements can give information about the fracture network even
before the tracer has reached the production wells. Once the tracer is injected into the reservoir, the electric potential difference between the injector and the producers decreases, and it continues to decrease as the conductive fluid flows through the fractures. The tracer return curves will not give any information about the network until the tracer has reached the producers. The inverse analysis was performed for 50 reservoirs, using only the electric and tracer data for 25 days of injection instead of the 70 days used previously. Figure 8.14 demonstrates the temperature estimation after 15 years in Producer 1 and Producer 2, and after 30 years in Producer 3. The coefficients of determination are shown in Table 8.11. For all the producers, the coefficient of determination is considerably higher when the electric approach is used to predict the thermal breakthrough time than when only the tracer measurements are used. Thus, the electric approach is better for estimating the thermal breakthrough time if performing the test for a shorter time is important and if results are needed quickly.

<table>
<thead>
<tr>
<th></th>
<th>Electric approach</th>
<th>Tracer approach</th>
</tr>
</thead>
<tbody>
<tr>
<td>R² for Producer 1:</td>
<td>0.78</td>
<td>0.58</td>
</tr>
<tr>
<td>R² for Producer 2:</td>
<td>0.52</td>
<td>0.22</td>
</tr>
<tr>
<td>R² for Producer 3:</td>
<td>0.38</td>
<td>0.00</td>
</tr>
</tbody>
</table>
Figure 8.13: The time [days] at when the temperature goes below 190 °C in a) Producer 1, b) Producer 2, c) Producer 3. 30 examples were considered.
Figure 8.14: The temperature [°C] after 15 years in a) Producer 1, b) Producer 2, and after 30 years in c) Producer 3 when 25 days are used in the inverse analysis. 50 examples were considered.
8.7 Summary

This chapter described how the electric approach previously explained in Chapter 6 could be used to predict the thermal behavior in geothermal reservoirs. The approach was compared to using just the simple tracer return curves at the producers. The electric approach gave similar results to the tracer approach, but in some cases the tracer return curves gave a better estimation of the thermal behavior. When the electric curves are used to find the best match for the true reservoir, the time it takes for the conductive tracer to reach the production well, as well as the overall locations of the connected areas are matched. However, when the injection scheme well pattern is the same as when the tracer test is performed, the overall location of the fractures might not be as important as the tracer breakthrough time. Thus, if a network that matches well both the tracer breakthrough time and the overall location of the fractures does not exist in the library of networks, the tracer return curves might a give better result for the thermal prediction. The possibility of using the electric measurements and the tracer return data combined in an inverse analysis was investigated. The results were in some cases better, but for other cases very similar to using only the tracer return curves or only the electric curves.

The electric and tracer return methods were also tested for a different injection scheme using a different well pattern. The electric method predicted the thermal behavior in the reservoir better than the tracer return method when fluid was injected from a different well than that used during the tracer and electric measurements. Additionally, the electric approach predicted the thermal behavior considerably better when measurements over only 25 days instead of 70 days were used. Thus, the electric
measurements characterize the overall location of fractures better than the tracer return curves, and can be more useful if quick results are needed.
Chapter 9

Conclusions and Future Work

This work has provided a method for characterizing fractures in geothermal reservoirs using time-lapse electric data. The method would consist of injecting a conductive fluid into a geothermal reservoir while measuring the electric potential difference between all well pairs. The electric potential difference between the wells drops as the conductive fluid fills the fracture paths in the reservoir. Thus, the changes in electric potential difference with time correspond to the characteristics of the fracture network.

An inverse analysis was performed to compare the time-lapse electric potential data for a geothermal reservoir to the electric potential data for a number of fracture networks in a library of fracture networks to find the best match. The best match could then be used to estimate the fracture characteristics of the true reservoir and predict the thermal behavior. The knowledge of the fracture distribution and estimated thermal behavior can help with the designing of an optimal recovery strategy that maximizes the overall efficiency of the power production. The fracture characterization process was repeated for various
reservoirs. In this chapter the main conclusions of this work are summarized and recommendations for future work are provided.

9.1 Conclusions

The connectivity of fractures in geothermal systems is a key factor in interpreting fracture flow to ensure adequate supply of geothermal fluids and efficient thermal operation of the wells. Currently, none of the geophysical exploration methods used to explore geothermal reservoirs is capable of providing an accurate high resolution model of the reservoirs at the required scale, depth and cost for running the power plants in an optimal way. The objective of this work was to investigate ways to characterize fractures in geothermal reservoirs and predict the thermal return which would give valuable information for designing an optimal recovery strategy. The electrical resistivity method was chosen for this study because it has a good potential for detecting water-filled fractures in the reservoirs due to the large contrast in resistivity between rock and water. The reinjection of waste water that is elevated in chloride acts to enhance the contrast in resistivity between rock and fracture zones. The electrodes would be placed inside geothermal wells to obtain a good depth resolution.

In this study, two methods were used for calculating electric fields, one using a structured-grid resistivity model and another using a flow simulator. Flow simulators TOUGH2 and General Purpose Research Simulator (GPRS) were both used successfully to calculate the electric fields of discrete fracture networks. TOUGH2 was used to study how the changes in salinity of the fluid in geothermal reservoirs affected the electric potential difference between wells in the reservoir. As
more connected paths from the injector towards the producers were filled with conductive fluid, the electric potential dropped. The peaks of the derivative of the time-history of the electric potential corresponded to the times of new highly conductive paths being formed. Kriging was also used to map the apparent resistivity between well pairs as tracer was injected into a reservoir to locate the most connected areas. Another scenario was studied where the reinjected fluid was elevated in NaCl concentration continuously with time. Results showed how the changes in electric potential due to the injection of conductive fluid could indicate connected fractures in the reservoirs.

The next step in investigating a way to use time-lapse electric potential to characterize fracture networks was to generate a library of discrete fracture networks with varying spatial fractal dimensions and use GPRS to simulate the flow of a conductive fluid through the reservoirs. GPRS was also used to solve the electric field at each time step while the fluid flows from the injector towards the producers. Then, an inverse analysis was introduced for finding a fracture network in the library of networks that best represents the fractured reservoir under study by comparing the time-lapse electric potential data. Four fracture characterization indices were provided for describing the character of the fractured reservoirs; the fracture density parameter, fractal dimension, fractional connected area, and the connectivity index. The goal was to find an index that was representative of the fluid movement through the fracture network so it could be used to model and predict the energy extraction in the reservoir. In this study, the fractional connected area and spatial fractal dimension were found to be most useful because these
indices captured the spatial distribution of fractures and sensitivity analyses showed correlations between the indices and the time-history of the electric fields.

For most of the cases studied, the fractional connected area and spatial fractal dimensions were predicted correctly using the inverse analysis with the time-lapse electric data. The locations of the connected areas were also predicted well so the method could be powerful for estimating the distribution of fractures in geothermal reservoirs. The fractional connected area was sometimes over- or underestimated due to fractures that increased the connected area but did not contribute to the flow, or fractures contributing to the flow but not intersecting other fractures. The spatial fractal dimension was also over-or underestimated if fractures not contributing to the flow occurred in the reservoir or the best match. However, in all cases the electric curves did predict the flow behavior in the reservoir correctly. For comparison, the fractures in the reservoirs were also characterized using only the simple tracer return curves at the producers in the inverse analysis instead of the electric data. The tracer return curves did in some cases predict the fractional connected area and the spatial fractal dimension correctly but the prediction using electric curves was more accurate. The locations of the connected areas were estimated well using the electric curves but the locations of connected areas estimated using tracer return curves were often incorrect. The tracer return curves are only measured at the producers while the electric data is measured between all well pairs, thus providing more extensive spatial information.

The possibility of using the electric approach to predict thermal behavior in geothermal reservoirs was investigated and was compared to using just the simple tracer return curves at the producers. The electric approach gave similar results to
the tracer approach, although in some cases the tracer return curves gave a better estimation of the thermal behavior. When the electric curves are used to find the best match for the true reservoir, the time it takes for the conductive tracer to reach the production well, as well as the overall location of the connected areas are matched. However, when the injection scheme is the same as when the tracer test is performed, the overall location of the fractures might not be as important as the tracer breakthrough time. Thus, if a network that matches well both the tracer breakthrough time and the overall location of the fractures does not exist in the library of networks, the tracer return curves might give a better result for the thermal prediction.

The possibility of using the electric measurements and the tracer return data together in an inverse analysis was also investigated. The results were in some cases better, but for other cases very similar to using only the tracer return curves or only the electric curves. The electric and tracer return methods were also tested for a different injection scheme with a new well pattern. The electric method predicted the thermal behavior in the new configuration better than the tracer return method when fluid was injected at a different location than the injection well that was used during the tracer and electric measurements. Additionally, the electric approach predicted the thermal behavior considerably better when measurements over only 25 days instead of 70 days were used. Thus, the electric measurements characterize the overall location of fractures better than the tracer return curves, and can be more useful if results are needed quickly.
9.2 Recommendations for Future Work

There are many avenues for extending the work in this dissertation and improving the electric method described for characterizing fractures in geothermal reservoirs. One such avenue would be to improve the fracture network library. A network library with more fracture networks could be provided. That way, the possibility of finding a good match that matches both the tracer breakthrough time and the location of the connected areas is increased. Fracture networks with different spatial and length distributions of fractures could also be included in the library to increase the possibility of finding a good match for geothermal reservoirs where fracture distributions might not be fractal. The drawback of increasing the fracture networks in the library of networks is the corresponding increase in computer power needed to simulate the flow of conductive tracer and solve the electric fields for all the networks. In addition, more time would be needed for the inverse analysis to compare the reservoir output to all the networks in the library to find the best match. If the number of networks becomes very large, the grid-search algorithm in the inverse analysis might not be feasible and a genetic algorithm could be better fitted to find the best match.

Another recommendation for future work is to extend the electric method to three dimensions. A three-dimensional model could be necessary to model the flow through natural three-dimensional fracture patterns. If a fracture connecting an injector and a producer is inclined with respect to a two-dimensional plane, only a part of the fracture would be included in the two-dimensional plane. However, the electric current would flow through the most conductive path and indicate a connection between the injector and the producer. Thus, the electric measurements would correspond to
the true fracture pattern in the reservoir but the two-dimensional plane under study might not be represented correctly. If the model was extended to three dimensions, it would be interesting to study different electrode layouts such as:

1. Electrodes placed at different depths inside the wells and record the electric potential difference between all electrodes.

2. Electrodes placed at different locations on the surface. Placing the electrodes on the surface might increase the spatial solution close to the surface but the depth resolution would be decreased.

3. Electrodes placed at different depths inside a well while other electrodes are placed at different locations on the surface.

A three-dimensional fracture model might be more representative of natural fracture patterns but solving the inverse problem in three dimensions requires a huge parameter space which could make it ill-posed. However, with future improvements in hardware, fast three-dimensional simulation of the fluid and electric flow in fracture networks should be possible.

Finally, there are some challenges remaining in designing and implementing the electric approach in practical settings. In addition to the injected current and changes in electric conductivity of the injected fluid, other factors could affect the electric potential measurements in geothermal reservoirs. For example, there are potential differences occurring naturally in the earth as measured in self-potential surveys. The potential is caused by the fluid flow through the porous medium and ion exchange between the fluid and soil particles. The voltage anomalies are relatively small but it could be interesting to incorporate self-potential in the model and study its effects on
the electric fracture characterization method. In addition, testing the effectiveness of the approach in practice is important. Various measurement errors could occur and it would be important to test whether the changes in electric potential as the conductive fluid flows through the fracture network are high enough to be detected between wells placed far apart. The conductivity of the well casing could also be a problem but studies have demonstrated that steel casings have been used as electrodes for resistivity measurements [73]. The salinity of the brine in the reservoir also affects how much the resistivity changes when a conductive fluid is injected into the reservoir. If the salinity of the brine is very high, one possible approach would be to inject low-saline water. That way, the resistivity would increase instead of decrease but the changes in resistivity would be detectable.
Bibliography


BIBLIOGRAPHY


