DEVELOPMENT AND TESTING OF ARTIFICIAL NEURAL NETWORK BASED MODELS FOR WATER FLOODING AND POLYMER GEL FLOODING IN NATURALLY FRACTURED RESERVOIRS

A Thesis in
Energy and Mineral Engineering
by
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Submitted in Partial Fulfillment of the Requirements for the Degree of

Master of Science

August 2015
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ABSTRACT

The increasing demand for energy and accelerated consumption of hydrocarbon fuel have made it a necessary objective for the oil and gas industry to continuously search for ways to improve and maximize recovery from oil reservoirs, to meet this growing global demand. Water flooding is one of the most common secondary recovery practices used in the petroleum industry to maintain reservoir pressure and improve oil displacement efficiency and recovery. Nonetheless, water flooding could pose several production problems in certain types of naturally fractured reservoirs, jeopardizing the overall sweep efficiency and oil recovery in the field. The presence of these heterogeneous natural fracture systems highly influences and complicates fluid flow process in the reservoir’s transport media. These fractures provide easy conduits and fluid pathways for the injected water, causing early premature water breakthrough, excessive water production and rapid decline of oil rate.

The implementation of polymer gel treatments is one of the viable solution commonly used in the industry to mitigate sweep conformance problems and improve oil recovery from naturally fractured reservoirs. Water-soluble polymer solutions are combined with cross-linking agents to form an in-situ gel that can be injected with water into the reservoir media. This polymer gel not only improves the overall mobility ratio of injected fluid, but also provides a mean to plug the conduit fractures and subsequently improving overall volumetric sweep efficiency and oil recovery from the reservoir matrix.

Reservoir simulators are commonly used to build reliable reservoir models for the purpose of history matching, production forecasting and evaluation of various design scenarios. Nonetheless, reservoir simulation can become very computationally demanding and time-consuming process. This problem could be overcome by the development of Artificial Neural
Network (ANN) models that could be used to generate various possible scenarios at a much efficient time pace compared to reservoir simulation.

The main objective of this research is to develop neuro-simulation proxy models for the implementation of water flooding and polymer gel flooding in naturally fractured reservoirs. Three main ANN models, one forward and two inverses, were developed for each scenario, water flooding and polymer gel flooding.

The first ANN, Forward ANN, provides a forward solution to predict the production profiles of oil rate, water cut and recovery factor for a given set of reservoir and design data. Forward results were matched within a desired tolerance of 10%. The second ANN, Inverse ANN-1, provides an inverse-looking solution to estimate the project design parameters required to produce a given production profile for a given set of reservoir properties. Five design parameters were investigated, including: reservoir’s drainage area, injection rate, producer bottom-hole pressure, polymer concentration and cross linker concentration. The last ANN, Inverse ANN-2, can be used as a tool for history matching and estimation of reservoir properties given a production profile and project design parameters. The reservoir properties predicted by this model include: matrix and fracture porosity, matrix and fracture permeability, fracture spacing, reservoir thickness and initial water saturation. The results from inverse ANN models were produced with an average error of 5 to 10%, per design parameter, and an average error of 8 to 28%, per reservoir property. Collectively, a total of six ANN tools were developed for the purpose of this research and were all encapsulated in a user-friendly Graphical User Interface (GUI) environment, to allow the end users for an easy access and utilization of these expert tools.
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ACKNOWLEDGEMENTS

I begin in the Name of Allah, The Beneficent, The Merciful, for all praise and glory belongs to Him.

I would like to express my sincere appreciation and gratitude to my thesis advisor, Dr. Turgay Ertekin. This research would not have been completed without his continuous guidance, generous support, patience and kindness. I am very proud and honored to be his student and I am forever grateful to have known him and worked with him. I would like also to thank, Dr. Morgan and Dr. Pisupati, for taking the time to serve as committee members.

In addition, I would like to thank Saudi Aramco Oil Company for providing me with this opportunity to pursue my master degree at the Pennsylvania State University.

Furthermore, sincere gratitude goes to my dear friends in State College, for their wonderful company throughout my study.

Finally, I would like to dedicate this work to my loving kind parents, my father Abdalraouf and my mother Ebtissam, for their unconditional love, endless sacrifice and support. For they are the most precious gift a son could ever have and everything I have is for them.

Mohammed Alghazal

University Park, Pennsylvania

August, 2015
Chapter 1

Introduction

In the oil and gas industry, there has been a growing interest in maximizing hydrocarbon recovery from existing resources to meet the world’s vast demand for energy and fuel. Over the years, various recovery methods and technological advances have been developed to increase oil production and improve its recovery. Water flooding is one of the most common and practical secondary recovery methods used in the industry to improve the displacement efficiency of oil and conserve the reservoir’s energy and pressure. Nonetheless, in certain types of naturally fractured reservoirs, water flooding operation could have many production problems if not managed properly, leading to poor oil sweep efficiency and ultimately low recovery. In such reservoirs, the fractures provide easy conduits and fluid pathways for the injected water, causing early premature water breakthrough, excessive water production and rapid decline of oil rate.

Polymer gel treatments are commonly used in the industry to mitigate sweep conformance problems in highly fractured reservoirs. A combination of polymer and cross linking agent solution can be injected with water to form an in-situ gel that can be used to both improve the mobility ratio of the injected fluid and most importantly to plug these conductive fractures. Consequently, this can significantly improve the overall volumetric sweep efficiency and oil recovery from the reservoir matrix by diverting the injected fluid from the conduit fractures.

Reservoir engineers frequently use reservoir simulation tools to build reliable reservoir models that can be used for history matching and production forecasting. However, reservoir simulation can become very computationally demanding, particularly for advanced thermal simulators which are required for chemical flooding, and it is also a time-consuming process.
Furthermore, reservoir simulation requires highly skilled individuals who have a competent knowledge in various fields, such as mathematics and computer programming. Nowadays, there has been a rising interest for using intelligent expert systems and neural networks to solve non-linear complex problems in various fields, such as reservoir simulation. Artificial Neural Networks, or ANNs, could be used to investigate and evaluate many possible production and reservoir scenarios at a much efficient time pace and speed compared to complex thermal reservoir simulators.

In this research, the development of neuro-simulation expert systems is thoroughly presented for the implementation of water flooding and polymer gel in naturally fractured reservoirs. CMG\textsuperscript{1} STARS\textsuperscript{2} thermal commercial simulator (version 2012.20) was used to build the reservoir model and generate various possible reservoir systems and production cases to feed them into the neural network. MATLAB\textsuperscript{3} tool box was used as a platform to train the generated data set and develop the proxy ANN models. A total of six ANN models were developed for two main cases: water flooding and polymer gel flooding. Mainly three ANN models were designed for each case: Forward ANN, Inverse ANN-1 and Inverse ANN-2. The first model is a forward-looking model which can be used to generate production profiles for a given set of reservoir properties and design parameters. The other two ANNs are inverse-looking and backward models, which can be used to estimate the project’s design parameters and reservoir properties, for Inverse ANN-1 and Inverse ANN-2 respectively, for a given production profile.

This research is mainly dissected into seven chapters. Chapter 2 provides an overview of the literature of naturally fractured reservoirs, polymer gels and neural networks. Chapter 3

\textsuperscript{1} CMG: Computer Modeling Group

\textsuperscript{2} STARS: Steam Thermal & Advanced Processes Reservoir Simulator

\textsuperscript{3} MATLAB: MATrix LABoratory
highlights the problem statement and workflow of this research. Chapter 4 provides an assessment and detailed description of the reservoir simulation models developed in this research. Chapter 5 thoroughly discusses the development of the ANN proxy models and presents an in-depth analysis of the generated results. Chapter 6 demonstrates the development of the Graphical User Interface (GUI) for the developed proxy models in Chapter 5. Finally, Chapter 7 highlights the main conclusions and recommendations derived from this study.
Chapter 2

Literature Review

In this chapter, several reservoir engineering aspects of naturally fractured reservoirs, polymer augmented water flooding and gel conformance treatments are reviewed from literature, focusing on its mechanism and field applications. Furthermore, the concept of Artificial Neural Network (ANN) and its applications are also discussed in this chapter.

2.1 Naturally Fractured Reservoirs

2.1.1 Introduction

From a reservoir engineering’s perspective, a natural fracture could be defined as a macroscopic planar discontinuity in a rock that occurred naturally due to a deformation or a physical diagenesis process (Nelson, 2001). Naturally fractured reservoirs consist of several networks of fractures and matrix that are randomly distributed within the reservoir (Bahrami, Rezaee, & Hossain, 2012). In addition, naturally fractured reservoirs are significant contributors to the global hydrocarbon reserves and production (Allan & Sun, 2003).

Unlike conventional reservoirs, reservoir characterization and production management from fractured reservoirs could be very challenging due to its high geological complexity and heterogeneity. Depending on the type of the fracture, these natural geological features could have a positive or negative impact on fluid flow within the reservoir, thus, affecting the reservoir’s ultimate recovery if not managed or characterized properly. Therefore, it is necessary to characterize and detect these fractures during different exploration and production stages using
several evaluation techniques such as, 3D seismic mapping, drill stem and pressure tests, image logs, well testing and core analysis (Nelson, 2001). Additionally, effective combination of good reservoir management practices have to be used in oil fractured reservoirs to better manage and deplete the field to prevent premature water breakthrough or excessive pressure and rate decline (Allan & Sun, 2003). The use of horizontal drilling technology and polymer-gel conformance treatments are both good examples of common reservoir practices used in the industry to mitigate the high influence of fractures on the fluid transport media. The latter strategy is the subject of this research and will be discussed in further details in the next section.

2.1.2 Classification and Simulation of Naturally Fractured Reservoirs

Naturally fractured reservoirs could be classified into four types based on its flow pathway contribution and storage capacity (Nelson, 2001). Type 1 reservoir is characterized by having very low matrix porosity and permeability, making the fractures the prominent storage and flow components providing both the essential porosity and permeability within the media. Fractures in Type 2 reservoirs also provide the storage and fluid pathway, however, the matrix has some storage or porosity contribution in the media. In Type 3 reservoirs, the matrix has high porosity and the reservoir is produced from the matrix, however, fractures assist in fluid flow providing flow pathway and permeability due to low matrix permeability. On the other hand, Type 4 reservoirs have both high porous and permeable matrix, providing both storage and fluid pathway. Consequently, fractures in Type 4 reservoirs could complicate fluid flow within the media by enhancing the permeability and creating significant reservoir anisotropy or barriers. Figure 2-1 shows a schematic cross plot which can be used to distinguish between these four types (Nelson, 2001). Type 4 reservoirs are the fractured reservoirs under interest in this study, where the
introduced gel targets these fractures to plug them and prevent them from causing an excessive water production jeopardizing oil recovery in the field.

Figure 2-1: A schematic cross plot showing types of fractured reservoirs (Nelson, 2001)

In reservoir modeling and simulation, Warren-Root and Kazemi geometric models are the most common early representations of fractured reservoirs in reservoir simulation (Bahrami et al., 2012). These models assume a set of discrete matrix blocks that are separated by orthogonal continuous system of fractures (Kazemi, Merrill Jr, Porterfield, & Zeman, 1976). Figure 2-2 below shows a graphical representation of these models.

Figure 2-2: Warren-Root and Kazemi’s fractured models (Bahrami et al., 2012)
Generally, there are two types of grid models for naturally fractured reservoirs in modern reservoir simulation packages: dual-porosity and dual-permeability models (Computer Modeling Group Ltd, 2012). Dual-porosity models assume that the fractures are the essential components responsible for fluid flow into the wellbore having low permeable matrix. Therefore, fluid flows from the discrete matrix blocks into the fractures and consequently towards the wellbore in dual porosity models. On the other hand, in dual-permeability models both the fracture and matrix components provide a mean for fluid and heat transfer within the media and towards the wellbore. Hence, dual-porosity models can be used to model Type I-III fractured reservoirs, whereas, Type IV can be modeled using dual-permeability models. Figure 2-3 demonstrates the difference between dual-porosity and dual-permeability models in terms of fluid flow direction as captured in reservoir simulation. As can be seen in Figure 2-3, the matrix blocks are not connected in the dual-porosity model as opposed to the dual-permeability model.

![Image of dual-porosity and dual-permeability models](Computer Modeling Group Ltd, 2012)

**Figure 2-3:** Representation of dual-porosity model (left) and dual-permeability model (right)
2.2 Polymer Augmented Water flooding and Gel Conformance Treatment

2.2.1 Polymer Augmented Water flooding

Water-soluble polymers have a variety of applications in the oil and gas industry. For instance, they are used as drilling additives, diverging agents and fluid loss additives (Argabright, Rhudy, & Trujillo, 1986). In reservoir engineering’s applications, they are also most commonly used for improving and enhancing oil recovery beyond secondary recovery processes. For example, polymer-augmented water flooding process is used to improve overall sweep efficiency and oil recovery in selectively high water-to-oil ratio fields and polymer-surfactant flood is most commonly used to enhance the recovery of residual oil left behind the water flood front (Argabright et al., 1986). Furthermore, these polymers are also mixed with cross-linking agents to form an in-situ polymer-gel that can be used for conformance treatment applications to improve recovery from highly fractured reservoirs. The process of forming this polymer-gel and its fields applications are discussed further in the next sections.

There are essentially two types of polymers used in the application of polymer flooding: Partially Hydrolyzed Poly-Acrylamides (PHPA) and biopolymer or xanthan gum (Argabright et al., 1986; Du & Guan, 2004). PHPA is a synthetic condensation polymer with a relatively high molecular weight’s range. On the other hand, biopolymers are derived from fermentation processes and have a lower molecular weight’s range than PHPA. PHPA is used for the conformance treatment process due to its ability to adsorb on the rock surface to produce a long-lasting permeability reduction effect, whereas biopolymers can’t be retained on rock surfaces (Du & Guan, 2004). Furthermore, PHPA is relatively cheaper and more cost-effective for wide field applications compared to biopolymers (Du & Guan, 2004). The molecular structure of PHPA consists of repeating units of [-CH₂-CH (CONH₂)-]. Figure 2-4 shows the molecular structure of PHPA.
The mechanisms of which polymer-augmented water flooding processes can improve oil recovery are not yet fully understood (Argabright et al., 1986). Nonetheless, it is commonly known that adding water-soluble polymer to injected water can significantly increase water viscosity. Hence, this can reduce the water-oil mobility ratio and consequently improve the overall volumetric sweep efficiency and oil recovery in the field (Argabright et al., 1986; Du & Guan, 2004). Reservoir rock and fluid properties are important factors that can affect the success of any potential polymer project. In fact, there are various guidelines and screening criteria that are published in the literature to identify the best reservoir candidates for polymer flood projects (Du & Guan, 2004; Saleh, Wei, & Bai, 2014). Screening tools include oil gravity, oil viscosity, oil saturation, porosity, permeability, reservoir temperature and depth (Saleh et al., 2014). Figure 2-5 below shows a comparison of different polymer flooding screening criteria as found in different works in the literature (Saleh et al., 2014). The most important screening criteria is reservoir temperature due to the effect of polymer viscosity degradation at high temperature. In most cases, it is recommended to have a reservoir temperature of less than 200 °F to have a successful polymer project (Saleh et al., 2014). Examples of successful field applications of full-field polymer-augmented water flooding include the Captain Field in the North Sea and Wyoming’s Big Horn Basin and Byron Fields (DeHekker, Bowzer, Coleman, & Bartos, 1986; Osterloh & Law, 1998).
2.2.2 Polymer Gel Conformance Treatment

In several field applications, polymer solutions are mixed with cross-linking agents to form an in-situ polymer gel that can be used to treat common reservoir conformance problems. This polymer gel technology was first developed in late 1984, when a mixture of Partially Hydrolyzed Poly-Acrylamide water solution, PHPA, cross linked with a Chromium III [Cr\(^{3+}\)] crosslinking agent (Sydansk, 1988). The Chromium’s crosslinking agent consists of a complex mixture of Cr\(^{3+}\) ions and carboxylate anions, such as acetate (Sydansk, 1988). Such gel system is often referred to in the literature as CC/AP gel or Cr(III)-Carboxylate/Acrylamide-Polymer (Sydansk & Southwell, 1998).

The main objective of this polymer gel is to act as a permeability reduction or plugging agent to improve oil recovery in reservoirs with sweep conformance problems (Sydansk & Southwell, 1998). There are many reservoir conformance problems that can be addressed and treated using this gel technology. The most common conformance problem is fractured reservoir anomalies, with or without direct fracture communication between injection and production wells.
CC/AP gels can be selectively injected within the region between the injectors and producers to selectively treat and plug fractures with high-permeability anomalies to improve sweep efficiency and oil recovery from the producible matrix (Sydansk & Southwell, 1998). In addition, polymer gels can be used to fluid-shut-off selective watered-out reservoir layers or thief zones in producers near the wellbore region (El-karsani, Al-muntasheri, & Hussein, 2014; Sydansk & Southwell, 1998; Sydansk, 1988). The difference between the two treatments is that the fracture-conformance problem requires relatively larger volume of gels with higher molecular weight polymers (Sydansk & Southwell, 1998). Collectively, these gel treatments are often called, Conformance-Improvement-Treatments or CITs (El-karsani et al., 2014; Sydansk, 1988). Generally, successful CITs operation results in diverting fluid flow from high-permeable zones with low-oil saturation to low-permeable zones with high oil saturation, thus improving overall sweep efficiency, flow conformance and ultimately oil recovery.

Many laboratory experiments and field studies were conducted over the years to comprehend the mechanism and operational feasibility of polymer gels. For instance, it has been shown that polymer gel strength and gelation time depend on many factors including, polymer type, polymer concentration and molecular weight, hydrolysis level, polymer-to-chromium ratio, temperature, polymer solution pH and salinity (Dang, Chen, Nguyen, Bae, & Phung, 2011; Sydansk, 1988). Consequently, these parameters have to be designed properly for each specific conformance treatment. In addition, Flooding experiments showed that gel propagation through fractures occurred after a minimum pressure gradient was achieved to extrude a given gel through the fractures (R. S. Seright, 1999). Furthermore, inter-well tracer and gel placement studies indicated that gel treatments become more effective in reservoirs with moderate to large fracture spacing (R. Seright & Lee, 1999). In the next section, examples of some field applications of polymer gels are highlighted.
2.2.3 Field Applications of Polymer Gels

Over the last decades, there has been a growing interest for using polymer gel conformance treatments in the oil industry. This interest is largely attributed to the fact that these treatments would highly improve sweep efficiency and oil recovery in problematic highly fractured and heterogeneous reservoirs without incurring high-end large capital costs (Sydansk & Southwell, 1998). Moreover, these treatments offer an economical solution for reducing excessive water production and handling costs in mature fields and managing CO₂ flood front movement in enhanced oil recovery operations with poor flood conformance (El-karsani et al., 2014; Sydansk & Southwell, 1998). Historical and modern applications of gel conformance treatments could be found across different fields worldwide such as the United States, South America and the Middle East.

Early application of polymer gel technology could be traced back to the Wyoming Big Horn Basin in the United States during the 1980’s. A total of 17 treatment jobs were applied in injection wells to improve sweep conformance from fractured carbonate and sandstone reservoirs (Sydansk & Southwell, 1998). It was estimated that these jobs have collectively resulted in an incremental oil recovery of more than 3 million barrels (Sydansk & Southwell, 1998). Moreover, CC/AP gel treatments were applied in Wertz field to improve sweep efficiency of CO₂ tertiary recovery from Tensleep fractured sandstone reservoir. It was reported that these treatments have resulted in an incremental oil recovery of about 140 thousand barrels per well pattern and also have extended the economic lives of many marginal wells for an extra two years (Sydansk & Southwell, 1998). Furthermore, polymer gel treatment was extensively used to improve sweep conformance from miscible CO₂ flooding operation at Rangely Weber Sand Unit in Colorado (Hild & Wackowski, 1999). This large polymer gel injection program was found economically viable
resulting in a payout period of 8 months and increasing incremental oil recovery by 21 barrels per day (Hild & Wackowski, 1999).

In South America, polymer gel treatments are extensively applied in Columbia, Venezuela and Argentina. In Columbia, polymer gel conformance treatments are used in Guando field to improve sweep conformance from the Guadalupe sandstone formation (Montoya et al., 2014). Initial water flooding operation at Guando field resulted in severe water channeling and sweep conformance problems due to the formation highly fractured and heterogeneous system. Therefore, polymer gels were injected at four pilot locations and un-adjacent injection patterns during the period between 2008 and 2013. An incremental recovery of more than 172 thousand barrels of oil was realized as a result of polymer gel treatments (Montoya et al., 2014). In Argentina and Venezuela, more than 100 polymer gel treatment jobs were applied to improve oil recovery from multi-layered reservoirs with cross-flow problems (Norman, Turner, Romero, Centeno, & Muruaga, 2006). Results were overall satisfactory in improving oil rate and reducing water production in most of these jobs. For instance, more than 200 thousand barrels of incremental oil was realized in the Vizcacheras field at Cuyana basin, as a result of polymer treatment (Norman et al., 2006).

In Saudi Arabia, polymer gel treatments are frequently used as a water-shut-off treatment to plug unwanted water-out intervals and thief zones to manage excessive water production and improve oil recovery (Nasr-El-Din et al., 1998). In Turkey, polymer gel treatment is used to improve sweep conformance from CO₂ flooding project in Bati Raman naturally fractured reservoir (Karaoguz, Topguder, Lane, Kalfa, & Celebioglu, 2007). An incremental increase of 12% of oil rate and payout period of 12 months were realized following the gel treatment in Bati Raman field (Karaoguz et al., 2007).
2.3 Overview of Artificial Neural Network

2.3.1 Historical Background

The modern view of artificial neural network came to light during the 1940’s by Warren MaCulloch and Walter Pitts (Hagan, Demuth, Beale, & Jesus, 2002). They have shown that artificial neurons could be employed to compute arithmetic or logical functions. Further development and application to this early concept was performed by Frank Rosenblatt in the late 1950’s, which marks the first golden age of neural networks (Fausett, 1994). Frank introduced the application of perceptron network, which consisted of an input layer connected to neurons by paths with fixed weights. He demonstrated that these networks could perform pattern recognition tasks. This has generated a great interest and wide recognition for neural networks applications at that time. Nonetheless, despite its early promise and success, the perceptron network was proven later to work for only limited class problems (Hagan et al., 2002). During the 1970’s, the progress and development of new artificial neural network ideas was very limited among the scientific community. This hiatus period was largely attributed to the slow progress in computation power at the time. Fortunately, there was a revived interest in neural network following the computational revolution that occurred during the 1980’s. There were mainly two new developed concepts that helped reinvigorating the field: the use of statistical mechanics to explain the operation of a certain class of recurrent network and the development of backpropagation algorithm for training multilayer perceptron networks. The latter development was mostly recognized by the work of David Rumelhart and James McClelland. Nowadays, the artificial neural network has a variety of powerful applications in various fields, such as: electronics, finance, banking, medical and oil and gas industry (Fausett, 1994; Hagan et al., 2002).
2.3.2 Model of Artificial Neurons

Artificial neural network is an information-processing system that attempts to mimic the functionality and complexity of the neural biological system (Shahab, 2000). The biological neuron is the fundamental building block of the nervous system which consists of mainly three parts: soma, dendrites and axon. The information, in the form of electrical signals, are received by the dendrites, processed by the soma and then passed to the axon. Similarly, the artificial neurons are the building blocks for the artificial neural network. The information comes to the artificial neuron via inputs, where each input is multiplied by a weighting function before entering the neuron. The neuron then sums the weighted inputs, bias and processes the sum via a transfer function before passing the information to the outputs (Suzuki, 2011). Figure 2-6 indicates the difference between biological and artificial neurons.

![Biological neuron (left) vs. artificial neuron (right) (Suzuki, 2011)](image)

The following equation describes the mathematical operation that occurs inside the artificial neuron (Suzuki, 2011):

\[ y_i(k) = F\left(\sum_{i=0}^{m} w_i(k) \cdot x_i(k) + b\right) \]

Where:

- \( x_i(k) \) and \( w_i(k) \) are the input value and weight value, respectively, in discrete time \( k \) where \( i \) goes from 0 to \( m \).
- \( F \) is the transfer function, \( b \) is bias and \( y_i(k) \) is output value in discrete time \( k \).
2.3.3 Artificial Neural Network Architecture

In most cases, using one artificial neural is not sufficient to solve complex problems. Therefore, it is often to find neurons combined and arranged in layers. The arrangement of these layers and connection between neurons define the artificial neural network architecture. There are typically two types of networks: a single layer network or a multilayer network. A single layer network contains only one layer, whereas, multilayer networks could have more than one layer. These layers are often referred to as hidden layers, as opposed to the input and output layer of the network. Figure 2-7 and Figure 2-8 demonstrate the difference between a single layer network and a multilayer network.

Figure 2-7: Example of a single layer network (Hagan et al., 2002)
The number of hidden layers and the number of neurons per layer depend on the complexity of the problem. It is essential to design the network to have the optimum number of layers and neurons to prevent under-fitting or over-fitting the data. It is often recommended to start with a simple design network and then add more hidden layers and neurons if needed (Beale, Hagan, & Demuth, 2014). Some authors attempted to come up with some rule-of-thumb methods that could be used to design the network’s structure. For instance, one of the rules states that the number of neurons in the hidden layers should not exceed twice the number of neurons in input layer and should be within 70-90% the size of both the input and output layers (Karsoliya, 2012). Nonetheless, these rules might not hold true for all problems and a trial and error approach should be used to find the optimum network architecture (Beale et al., 2014; Karsoliya, 2012).

2.3.4 Transfer Functions

Transfer functions are used to activate neurons and scale its response to an external stimulus (Maren, Harston, & Pap, 1990). Transfer functions could be linear or non-linear. The
selection of a transfer function depends on the complexity of the problem. In general, complex problems with multilayers network require the use of non-linear activation functions. Table 2-1 shows a variety of transfer functions’ examples (Hagan et al., 2002). The most common used transfer functions in multilayers networks are purelin and logsig transfer functions. Purelin transfer function is a linear function and it is most commonly used in the last output layer of a multilayer network. On the other hand, the logsig or log-sigmoid transfer function is a non-linear function, which scales output value to a range between 0 and 1. In this study, logsig function was found to be the most effective transfer function to be used in hidden layers of a multilayer feedforward backpropagation network.

Table 2-1: Transfer functions adapted from (Hagan et al., 2002)

<table>
<thead>
<tr>
<th>Name</th>
<th>Input/Output Relation</th>
<th>Icon</th>
<th>MATLAB Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hard Limit</td>
<td>$a = 0$ $n &lt; 0$ $a = 1$ $n \geq 0$</td>
<td><img src="image" alt="Hard Limit Icon" /></td>
<td>hardlim</td>
</tr>
<tr>
<td>Symmetrical Hard Limit</td>
<td>$a = -1$ $n &lt; 0$ $a = +1$ $n \geq 0$</td>
<td><img src="image" alt="Symmetrical Hard Limit Icon" /></td>
<td>hardlims</td>
</tr>
<tr>
<td>Linear</td>
<td>$a = n$</td>
<td><img src="image" alt="Linear Icon" /></td>
<td>purelin</td>
</tr>
<tr>
<td>Saturating Linear</td>
<td>$a = 0$ $n &lt; 0$ $a = n$ $0 \leq n \leq 1$ $a = 1$ $n &gt; 1$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Symmetric Saturating Linear</td>
<td>$a = -1$ $n &lt; -1$ $a = n$ $-1 \leq n \leq 1$ $a = 1$ $n &gt; 1$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log-Sigmoid</td>
<td>$a = \frac{1}{1 + e^{-n}}$</td>
<td><img src="image" alt="Log-Sigmoid Icon" /></td>
<td>logsig</td>
</tr>
<tr>
<td>Hyperbolic Tangent Sigmoid</td>
<td>$a = \frac{e^n - e^{-n}}{e^n + e^{-n}}$</td>
<td><img src="image" alt="Hyperbolic Tangent Sigmoid Icon" /></td>
<td>tansig</td>
</tr>
<tr>
<td>Positive Linear</td>
<td>$a = 0$ $n &lt; 0$ $a = n$ $0 \leq n$</td>
<td><img src="image" alt="Positive Linear Icon" /></td>
<td>poslin</td>
</tr>
<tr>
<td>Competitive</td>
<td>$a = 1$ neuron with max $n$ $a = 0$ all other neurons</td>
<td><img src="image" alt="Competitive Icon" /></td>
<td>compet</td>
</tr>
</tbody>
</table>
2.3.5 Learning Methods and Training Algorithms

Based on training methods, neural networks could be classified into two major categories: unsupervised and supervised learning. Unsupervised learning are mainly clustering and classification algorithms, in which the network receives no output feedback and is provided with input vectors to classify them into groups and clusters (Shahab, 2000). In the oil and gas industry, unsupervised learning is used to interpret well logs data and lithology (Shahab, 2000). On the other hand, neural networks with supervised training algorithms requires both input and output data to learn on a feedback basis. In supervised learning, weights are initialized randomly and then iterated until a reasonable match is achieved between the calculated outputs and the network’s desired targets. In most oil and gas applications and also in this research, feed forward network with backpropagation supervised learning algorithm is used. Feed forward network requires the interconnection between layers and flow direction to flow from the input to the hidden layers to the output layer, respectively (Badde, Gupta, & Patki, 2009). The backpropagation algorithm is a gradient descent method that minimizes the total error between the network’s outputs and desired targets by adjusting weights and biases using a generalized rule of the Least Mean Squared (LMS) error (Fausett, 1994).

MATLAB neural network tool provides a variety of training algorithms for multilayer feed forward backpropagation networks. The default training algorithm used is called, \textit{trainlm (Levenberg-Marquardt)}, however this algorithm is not suitable for training large complex data set, as in this case. For large data set, \textit{trainscg (Scaled Conjugate Gradient)} and \textit{trainrp (Resilient Backpropagation)} are more frequently used, which both have relatively small memory requirements and efficiently perform much faster compared to other algorithms (Beale et al., 2014). The training algorithm \textit{trainscg} was found to be the most efficient choice for this study.
2.3.6 Generalization and Early Stopping

Generalization is the most desired learning outcome of a network as opposed to memorization. Memorization occurs due to over-fitting causing the network to memorize instead of learning and generalizing the data. In order to avoid such a problem, the network data set is randomly divided into three parts: training, validation and testing. The validation set can be used to check and monitor the performance of the network. Initially, the error of both the training and validation set starts to decrease as the network continues to iterate. However, when the validation error starts to increase and training error starts to decrease, this is an indication of network memorization. Hence, validation error must be monitored and training should be stopped when memorization behavior occurs. This technique is called early stopping and it is one of the most common methods used to prevent over-fitting problems. The testing data set are not seen by the network and can be used to independently assess the performance of the network. Similarly, if testing error starts to increase, the network should be stopped. In addition, functional links are commonly used to enhance the training performance. Functional links are mathematical relations between input or output variables that could be used to strengthen the connection between network’s parameters.

2.3.7 Applications of Artificial Neural Network in the Oil and Gas Field

There has been a growing interest for using Artificial Neural Network (ANN) in the oil and gas field. The ability of ANN to solve complex non-linear problems in the absence of enough data has made it attractive for various applications in the petroleum market. For instance, ANN has been known to be used in seismic pattern recognition, permeability predictions, drill bit diagnosis and improvement of gas well production (Ali, 1994). Moreover, neural networks have several
applications in reservoir characterization to predict conventional image logs parameters such as porosity and fluid saturation and also non-conventional logs such as Nuclear Magnetic Resonance (NMR) (Shahab, 2000). Furthermore, the literature is rich with various ANN tools developed in many other different reservoir engineering’s areas such as, reservoir simulation, well testing, history matching and Enhanced Oil Recovery (EOR) (Arpaci, 2014; BuKhamseen, 2014; Gaw, 2014; Ma, 2010; Prada Minakowski, 2005). The following discussion provides an overview of the most recent works developed in the EOR field, which is the main subject of this research.

Prada (2005) developed an ANN tool-box that could be used as a screening tool for various hydrocarbon secondary and enhanced oil recovery techniques, including: water flooding, miscible CO₂ injection, nitrogen injection and steam injection. This tool allows the user to predict reservoir production performance and compare the results between many different EOR methods using different fluid mixture composition, rock properties and design parameters. The main design parameters used by Prada are well spacing, well pattern and well’s operation pressure. Ma (2010) developed a proxy model to analyze the performance of Water-Alternating-Gas (WAG) injection process. Ma (2010) expanded the work of Prada in the area of miscible CO₂ flooding of a five-spot pattern by including several design parameters for the assessment of miscible WAG processes, including: water-gas ratio, alternating frequency and alternating slug size. Arpaci (2014) developed a tool to assess the performance of a cyclic steam stimulation process of a horizontal well located in a naturally fractured formation. Arpaci included several new design and performance indicators in the assessment of cyclic steam flooding operations such as, cyclic production rates, horizontal well length, steam quality and temperature, soaking and injection period and fractured inner zone porosity, permeability and spacing. The results from this research can be added to this list of ANN tools developed in the area of Enhanced Oil Recovery (EOR) to include polymer gel flooding, which can be further expanded in future works considering the recommendations in Chapter 8.
Chapter 3

Problem Statement and Work Overflow

Water flooding is one of the most common secondary recovery mechanisms used in the petroleum industry following primary depletion to maintain reservoir pressure and improve recovery. Nonetheless, the implementation of water flooding practice in naturally fractured oil reservoirs poses numerous production challenges that could impact the overall ultimate recovery of the field. Unlike conventional reservoirs, the presence of this complex heterogeneous fractured system provides an easy conduit and fluid pathway for water, which could potentially lead to an early premature water breakthrough and rapid decline of oil rate. The use of polymer coupled with a cross linking agent to form an in-situ gel solution is one of the practical solution available to improve recovery in fractured reservoirs. This polymer gel not only improves the overall mobility ratio of injected fluid, but also provides a mean to plug the conduit fractures and subsequently improving overall sweep efficiency and oil recovery in the reservoir.

The use of reservoir simulators to build reliable reservoir models and evaluate various design scenarios and production profiles, can become computationally very complex and time-consuming process. This problem could be overcome by the development of an Artificial Neural Network (ANN), which could be used to evaluate several possible scenarios at a much efficient time pace. As discussed previously in Chapter 2, these ANN models have the capability of mathematically solving non-linear complex problems given a network of input and output data.

The main objective of this study is to build reliable ANN models for the assessment of both injecting only water and injecting polymer gel augmented water in various naturally fractured systems in a typical five spot pattern reservoir using different design parameters. The following
steps summarize the research workflow utilized to systematically develop these proxy ANN models, refer to Figure 3-1:

- Construct a representative reservoir model using a commercial thermal simulator and validate results.
- Generate various production scenarios using a combination of different reservoir properties and design parameters within a specified input data range.
- Collect all data in a form of matrix with both input and output parameters and validate data set.
- Feed the neural networks with the created data set and start training the network.
- Compare output results from the network to the synthetic simulator data and continuously evaluate the structure and network’s topography.
- If calculated errors are significantly high in several cases, analyze the production trends and their reservoir/design parameters, and add/remove cases to cover various trends if necessarily.
Build Initial Reservoir Model

Validate Initial Results

Collect Production Profiles for Each Case

Generate Different Cases of Input Reservoir and Design Data

Feed Data to ANN and Compare network output results with Simulator until a reasonable match is attained

Figure 3-1: Workflow Process Flow Chart
In this study, oil rate, water cut and recovery factor profiles were used as key performance indicators for all the cases. Various ranges of reservoir properties were used to generate these profiles which include, matrix and fracture porosity, matrix and fracture permeability, fracture spacing, reservoir thickness and initial water saturation. In addition, different ranges of project design data were used including: reservoir’s drainage area, injection rate, producer bottom-hole pressure and, in case of polymer gel flooding scenario, it also includes polymer and cross linker concentrations. These different combination of reservoir properties and project design parameters were generated randomly using MATLAB with a specified upper and lower range for each parameter, refer to Appendix A for properties’ distribution over all cases generated for the polymer gel flooding case.

Three main ANN models were developed for each scenario, water flooding and polymer gel flooding. The first ANN, Forward ANN, provides a forward solution to predict the production profiles for a given set of reservoir and design data. The second ANN, Inverse ANN-1, provides an inverse-looking solution to estimate the project design parameters required to produce a given production profile for a given set of reservoir properties. The last ANN, Inverse ANN-2, can be used as a tool for history matching and estimation of reservoir properties given a production profile and project design parameters, refer to Figure 3-2. Hence, a total of six ANN tools were developed for the purpose of this research. Moreover, a Graphical User Interface (GUI) was designed to combine these proxy models in a user-friendly accessible environment.
Figure 3-2: ANN Proxy models
Chapter 4

Reservoir Modeling

CMG STARS thermal simulator (version 2012.20) was used in this study to build the reservoir model and generate simulation results. The methods and various steps used to construct this model are discussed in further details in this chapter including: reservoir properties description, fluid components and adsorption properties, rock-fluid properties, and project design.

4.1 Reservoir Description

The reservoir is a three-dimensional dual-permeability Cartesian model. For each constructed model, the reservoir is assumed to be homogeneous with three layers of equal thickness. Figure 4-1 shows a three-dimensional cross section of the reservoir model. Furthermore, reservoir top was kept constant at 5000 ft and reservoir pressure and temperature were initialized at 4000 psia and 120 °F. Different ranges of other reservoir properties were used to build the model including: reservoir’s total thickness, matrix and fracture porosity, matrix and fracture permeability, fracture spacing and initial water saturation. The fracture permeability and spacing are isotropic, i.e. the same in all directions. For matrix permeability, a horizontal-to-vertical permeability ratio of 0.1 is assumed. The data set was generated using a random number generator function in MATLAB. Table 4-1 below shows the range of reservoir properties used to construct the model. These ranges of parameters were selected to reflect the screening criteria for polymer flooding projects, as discussed in section 2.2.1 (Saleh et al., 2014).
Figure 4-1: 3D cross section of reservoir model

Table 4-1: Range of reservoir properties used in the model

<table>
<thead>
<tr>
<th>Reservoir Property</th>
<th>Min</th>
<th>Max</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reservoir Thickness ($h$)</td>
<td>50</td>
<td>300</td>
<td>ft</td>
</tr>
<tr>
<td>Matrix Porosity ($\Phi_m$)</td>
<td>0.15</td>
<td>0.6</td>
<td>fraction</td>
</tr>
<tr>
<td>Fracture Porosity ($\Phi_f$)</td>
<td>0.0001</td>
<td>0.01</td>
<td>fraction</td>
</tr>
<tr>
<td>Matrix Permeability ($k_m$)</td>
<td>20</td>
<td>300</td>
<td>mD</td>
</tr>
<tr>
<td>Fracture Permeability ($k_f$)</td>
<td>400</td>
<td>3000</td>
<td>mD</td>
</tr>
<tr>
<td>Fracture Spacing ($d_f$)</td>
<td>33</td>
<td>328</td>
<td>ft</td>
</tr>
<tr>
<td>Initial Water Saturation ($S_w$)</td>
<td>0.1</td>
<td>0.3</td>
<td>fraction</td>
</tr>
<tr>
<td>Reservoir Temperature ($T$)</td>
<td>120</td>
<td>°F</td>
<td></td>
</tr>
<tr>
<td>Reservoir Pressure ($P$)</td>
<td>4000</td>
<td>psia</td>
<td></td>
</tr>
<tr>
<td>Reservoir Top ($d$)</td>
<td>5000</td>
<td>ft</td>
<td></td>
</tr>
</tbody>
</table>
4.2 Fluid Components and Gel Reaction

There are five types of fluid exist or injected into the reservoir: oil, water, polymer, cross-linker and gel. It’s assumed that all these components exist in an aqueous phase except for the oil where it partitions into an oleic phase. Table 4-2 shows the properties of these fluids components as presented in the model. Component properties are adapted from Scott, Roberts, Sharp, Clifford, & Sorbie (1987).

Table 4-2: Fluid components properties in reservoir model

<table>
<thead>
<tr>
<th>Fluid</th>
<th>Oil</th>
<th>Water</th>
<th>Polymer</th>
<th>Cross-linker</th>
<th>Gel</th>
</tr>
</thead>
<tbody>
<tr>
<td>Phase</td>
<td>Oleic</td>
<td>Aqueous</td>
<td>Aqueous</td>
<td>Aqueous</td>
<td>Aqueous</td>
</tr>
<tr>
<td>Molecular Weight, lb/lbmol</td>
<td>100</td>
<td>18</td>
<td>10000</td>
<td>206</td>
<td>10206</td>
</tr>
<tr>
<td>Density, lb/ft$^3$</td>
<td>50.0</td>
<td>62.4</td>
<td>62.4</td>
<td>62.4</td>
<td>62.4</td>
</tr>
<tr>
<td>Viscosity, cp</td>
<td>1.0</td>
<td>0.5</td>
<td>0.5</td>
<td>4.0</td>
<td>0.5</td>
</tr>
</tbody>
</table>

The in-situ gel, which is essentially responsible for plugging the fractures, is formed by considering a simple reaction mechanism between the added polymer and cross-linker, such that a 1 lbmol of polymer is reacting with 1 lbmol of cross-linker to produce 1 lbmol of in-situ gel (Scott et al., 1987). Figure 4-2 shows the chemical reaction properties as introduced in the reservoir model.

The fluid properties and chemical reaction are kept unchanged throughout the model due to the fact that these chemicals and their properties are highly temperature dependent and the reservoir temperature is assumed to be constant in the model.
4.3 Rock-Fluid Properties (Adsorption and Relative-Permeability Data)

Adsorption properties for both the polymer and gel components are populated into the model (Scott et al., 1987), refer to Table 4-3. As can be seen from Table 4-3, the Residual Resistance Factor (RRF), ratio between the fluid permeability before and after injecting the gel, for the formed in-situ gel is greater than the polymer, causing a significant reduction in effective permeability in the reservoir system and mainly acting as a plugging agent for the existing fractures in the reservoir model.

Table 4-3: Adsorption properties for polymer and gel components in matrix and fracture

<table>
<thead>
<tr>
<th>Fluid</th>
<th>Polymer</th>
<th>Gel</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Matrix Fracture</td>
<td>Matrix Fracture</td>
</tr>
<tr>
<td>Adsorption Capacity, lbmol/ft³</td>
<td>0.01364×10⁻⁴</td>
<td>0.0572×10⁻⁴</td>
</tr>
<tr>
<td>Residual Resistance Factor (RRF)</td>
<td>1.8</td>
<td>2.5</td>
</tr>
</tbody>
</table>
Water-oil relative permeability model was also adapted after Scotts (Scott et al., 1987). The relative permeability data used in the model assumes a water-wet system with relatively high permeable layers, as in the case of this model. Table 4-4 and Figure 4-3 display the relative-permeability data included in the model.

Table 4-4: Relative-Permeability Data (Scott et al., 1987)

<table>
<thead>
<tr>
<th>Water Saturation $(S_w)$</th>
<th>Relative Permeability to water $(k_{rw})$</th>
<th>Relative Permeability to Oil $(k_{r ow})$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.25</td>
<td>0</td>
<td>0.9</td>
</tr>
<tr>
<td>0.3</td>
<td>0.002</td>
<td>0.69</td>
</tr>
<tr>
<td>0.4</td>
<td>0.03</td>
<td>0.33</td>
</tr>
<tr>
<td>0.5</td>
<td>0.06</td>
<td>0.13</td>
</tr>
<tr>
<td>0.6</td>
<td>0.14</td>
<td>0.04</td>
</tr>
<tr>
<td>0.7</td>
<td>0.2</td>
<td>0.005</td>
</tr>
<tr>
<td>0.78</td>
<td>0.3</td>
<td>0</td>
</tr>
</tbody>
</table>

Figure 4-3: Relative Permeability Curve (Scott et al., 1987)
4.4 Project Design (Wells’ Configuration)

Two vertical wells are included in the model: a producer and an injector. The placement of these two wells is selected to reflect the position of one-fourth of a five spot injection pattern, refer to Figure 4-4. Hence, generated production profiles could be used to reflect the behavior of a polymer gel flooding or water flooding pilot with a five-spot pattern arrangement. A combination of five different design parameters with a specified range are used to generate the data set, including: drainage area, injection operation rate, producer flowing bottom-hole pressure, polymer concentration and cross-linker concentration. Table 4-7 shows the different ranges of design parameters used to generate the data set, as reviewed from the literature (Montoya et al., 2014; Norman et al., 2006; Sydansk & Southwell, 1998). The drainage area used in the data set was scaled up to directly reflect the area of the five-spot pattern.

![Figure 4-4: Five-Spot injection pattern](highlighted region depicts the reservoir model)

Table 4-5: Range of design parameters used in the model

<table>
<thead>
<tr>
<th>Design Parameter</th>
<th>Min</th>
<th>Max</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Injection Rate ( (q_w) )</td>
<td>100</td>
<td>5000</td>
<td>bbl/d</td>
</tr>
<tr>
<td>Producer Flowing Pressure ( (p_{wf}) )</td>
<td>3000</td>
<td>3700</td>
<td>psia</td>
</tr>
<tr>
<td>Drainage Area ( (A) )</td>
<td>5</td>
<td>30</td>
<td>Acres</td>
</tr>
<tr>
<td>Polymer Concentration ( (PLMR) )</td>
<td>1000</td>
<td>5000</td>
<td>ppm</td>
</tr>
<tr>
<td>Cross-linker Concentration ( (XLKR) )</td>
<td>100</td>
<td>500</td>
<td>ppm</td>
</tr>
</tbody>
</table>
4.5 Grid Block Sensitivity Analysis

Prior to generating the data set, it was necessary to perform a grid block sensitivity analysis to determine the optimum number of grids that should be used to construct the reservoir model. This is a very crucial preliminary step for simulation modeling. Generally, models constructed with a larger number of grid blocks give more accurate predictions and simulation outputs. However, adding more grid blocks comes at the expense of significantly increasing computation and simulation time.

Cumulative production data and simulation running time was compared using different grid sizes from 10×10 to 55×55, where the number of grids are the same in the x and y directions for each grid size. As can be readily observed from Figure 4-5, the cumulative production results start to level at a grid size of 25×25. In addition, the simulation time significantly starts to increase for larger grid sizes. Therefore, a grid size of 25×25 was used as an optimum grid size to construct all the models and generate the data set as it gives accurate production results combined with faster running time.

Figure 4-5: Grid sensitivity analysis
4.6 Validation Runs

Prior to start generating the data set and training the network, it was essential to establish several benchmark simulation runs to check the validity of the reservoir model and test its capability to improve field recovery by plugging the fractures and improving overall sweep efficiency through in-situ gel injection.

The approach was to run two main scenarios and compare the production results. The first scenario compares the difference between the injection of only water, water augmented with polymer and water augmented with polymer and cross-linker, i.e. in-situ gel, in a dual-permeability model. Table 4-6 and Table 4-7 show the set of reservoir properties and design parameters used to populate the models. Figure 4-6 and Figure 4-7 show a comparison of oil rate and water cut performance for all three cases. Figure 4-8 shows the difference in overall field recovery between the three cases. As can be clearly seen from these plots, the injection of in-situ gel outperforms all other cases by significantly doubling the oil recovery and delaying water breakthrough into the producer for almost one year. On the other hand, the injection of water and water with polymer both suffer from a rapid water breakthrough and decline in oil rate from the first year. Despite the fact that polymer injection can slightly improve oil recovery compared to water injection, it is still insufficient to make a significant impact on recovery, refer to Figure 4-8.

Table 4-6: Reservoir properties model specification

<table>
<thead>
<tr>
<th>Reservoir Property</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reservoir Thickness ($h$)</td>
<td>150</td>
<td>ft</td>
</tr>
<tr>
<td>Matrix Porosity ($\phi_m$)</td>
<td>0.2</td>
<td>fraction</td>
</tr>
<tr>
<td>Fracture Porosity ($\phi_f$)</td>
<td>0.01</td>
<td>fraction</td>
</tr>
<tr>
<td>Matrix Permeability ($k_m$)</td>
<td>100</td>
<td>mD</td>
</tr>
<tr>
<td>Fracture Permeability ($k_f$)</td>
<td>1000</td>
<td>mD</td>
</tr>
<tr>
<td>Fracture Spacing ($d_f$)</td>
<td>66</td>
<td>ft</td>
</tr>
<tr>
<td>Initial Water Saturation ($S_w$)</td>
<td>0.1</td>
<td>fraction</td>
</tr>
</tbody>
</table>
Table 4-7: Design parameters model specification

<table>
<thead>
<tr>
<th>Design Parameter</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Injection Rate ($q_w$)</td>
<td>4000</td>
<td>bbl/d</td>
</tr>
<tr>
<td>Producer Flowing Pressure ($p_{wf}$)</td>
<td>3000</td>
<td>psia</td>
</tr>
<tr>
<td>Drainage Area ($A$)</td>
<td>20</td>
<td>Acres</td>
</tr>
<tr>
<td>Polymer Concentration ($PLMR$)</td>
<td>1000</td>
<td>ppm</td>
</tr>
<tr>
<td>Cross-linker Concentration ($XLKR$)</td>
<td>100</td>
<td>ppm</td>
</tr>
</tbody>
</table>

Figure 4-6: Production performance for water (blue) and water-polymer (red) injection cases
Figure 4-7: Production performance for gel injection case

Figure 4-8: Recovery factor comparison for water (red), water-polymer (blue) and gel (green)
The second scenario is to compare the performance of water flooding and in-situ gel injection in a single-porosity reservoir model with no presence of fractures. The main objective of this approach is to confirm the capability of the gel of plugging the fracture system and not the high-permeable matrix. The properties used to build the model are similar to the ones outlined in Table 4-6 and Table 4-7, expect that there are no fractures present in the system. Figure 4-9 and Figure 4-10 show the production performance of water injection and in-situ gel injection in a single-porosity model. The production performance from the two scenarios are almost identical with no clear evidence of the effect of the gel to plug the matrix system by arresting and delaying the early water breakthrough as it was seen in Figure 4-7. In addition, Figure 4-11 demonstrates that there is only a slight improvement in overall oil recovery for the gel system compared to the improvement realized in the dual-permeability model in Figure 4-8.

These combined results from both scenarios give a clear indication of the capability of the current model to improve overall sweep efficiency and ultimately oil recovery in the naturally fractured reservoir by plugging or significantly reducing the permeability of the present fractures in the model.
Figure 4-9: Production performance in a water flooding single-porosity model

Figure 4-10: Production performance of gel injection in a single-porosity model
Figure 4-11: Field recovery comparison in a water (blue) and gel (red) single-porosity model

4.7 Collection of Results and Time Frequency

For each generated case, three performance indicators are collected over a specified time frequency: oil rate, water cut and recovery factor. The results are collected over a 10 years period. For the first two years, the data are collected every 15 and 30 days, respectively. For the remaining years, the data are collected every 90 days. It was desired to have a higher time resolution for the first two years to better capture the behavior of water breakthrough occurring at early production. In total, 68 data points were collected over the 10 years’ period for each performance indicator. In addition, an abandonment rate of 10 STB/D is considered for all cases. Figure 4-12 and Figure 4-13 show some examples of collected results of oil rate, recovery factor (RF) and water cut. In order to have a consistent number of data points and time frequency for all cases, data points after abandonment condition were set equal to the data point at abandonment time. However, these data
40 points were removed from display in the figures to eliminate redundancy as shown in Figure 4-13 and later plots in the next chapter.

Figure 4-12: Example of production data collected for Case-10 (gel scenario)
Figure 4-13: Example of production data collected for case-13 (gel scenario)
Chapter 5

Artificial Neural Network Development

After generating the data set and collecting simulation results, MATLAB neural network tool box was used to develop neuro-proxy models which can be used to predict reservoir production performance, project design parameters and reservoir properties for two different cases: water flooding case and polymer gel flooding case. In this chapter, the development of a total of six expert systems are presented and thoroughly discussed. Three Artificial Neural Networks (ANNs) were developed for each scenario, including: Forward ANN, Inverse ANN-1 and Inverse ANN-2. The Forward ANN model is developed to predict field’s performance and generate production and recovery profiles. On the other hand, Inverse ANN-1 and Inverse ANN-2 are inverse looking solutions developed to estimate project design parameters and reservoir properties, respectively.

The first section of this chapter provides an introductory guideline and general procedure that was used to develop these expert systems. The remaining sections are dedicated to discuss in depth the structure of each ANN system and detailed analysis of results for each case, water flooding case and polymer gel flooding case.

5.1 Introduction

The development of a satisfactory ANN model is a complex process that requires experimenting with several structures and algorithms and also adapt a systematic trial and error approach to reach the target optimum structure for a given problem with reasonable margin of error. Depending on the complexity of the problem and data set, the optimum network topography varies widely from one case to another. Nonetheless, the learning process is exponential, the developer becomes more expert with the network as time progresses and knows what works best for a given
data set and problem. The following provides a set of guidelines and general approaches that were taken into considerations to develop the proxy models in this study:

- **Number of dataset**: determining the optimum number of data set for a given problem requires the developer to know beforehand the various ranges of input data and different trends of production data available. In addition, supplying the network with unnecessary large data set could potentially lead to memorization and over-fitting problems. Therefore, it is important to generate a data set with an optimal number of cases. In this study, initially 500 cases were used to build the network for both cases water flooding and polymer gel. It was observed later that the Forward ANN model always fails to predict a common trend of production curves regardless of the ANN structure being used. After further analysis of these production trends, it was realized that these trends were mostly associated with low injection rate and low permeable systems. Therefore, more cases were generated to produce these trends and new batch of data were added to the original data set. Additionally, some non-practical cases were eliminated from the original set. After several investigations and optimization of data set, it was found that the optimum number of data set are 738 for the water flooding scenario and 1000 for the polymer gel flooding scenario.

- **Division of data set**: the two data sets were randomly divided into 90% for training, 5% for validation and 5% for testing, using dividerand function in MATLAB. The random division was to ensure the coverage of a wide range of input data without gathering similar reservoir or design parameters. The validation set was monitored closely throughout training, as discussed in Chapter 2, to prevent under-fitting or over-fitting the data. The error between the network output and desired target was
regularly evaluated for all testing cases and progressively improved via adjusting
the network’s topography and other parameters, such as functional links.

- **Training algorithm and transfer function:** the selection of a suitable training
  algorithm and transfer or activation function is an essential part to build the ANN
  model. A cascade feed forward network with a backpropagation scaled conjugate
  gradient training algorithm (*trainscg*) was found to produce better results
  compared to other available training algorithms provided in MATLAB’s tool box.
  Additionally, the log-sigmoid transfer function (*logsig*) was found to perform
  better than any other transfer function. Furthermore, gradient descent with
  momentum weight and bias (*learngdm*) was used as a learning algorithm and the
  performance of the network was controlled using the mean sum of squares of the
  network error with regularization performance function (*msereg*).

- **ANN structure (layers and neurons):** the determination of the optimum number of
  layers and neurons in a network structure is the most important task for ANN
  development and can become timely consuming and tedious. In order to efficiently
  optimize this process, a MATLAB code was developed to automatically generate
  several initial network structures by assigning a random number of neurons and
  layers to each structure. Then, the performance of these structures are compared
  against each other to estimate the best possible number of layers or total number
  of neurons for a given model or problem. Based on these initial insights, the ANN
  structure is then manually adjusted until an optimum number of hidden layers and
  neurons is found with the least offset error from the desired target. For instance, in
  this study, it was found that using five to six hidden layers generates the best results
  for the Forward ANN models compared to the Inverse ANN-1 models, which
  requires only one hidden layer to produce optimum results.
- **Number of epochs (iterations) and validation checks:** estimating the number of required epochs or iterations to train the network is one of the parameters that can be adjusted and optimized. The number of required epochs differ from one model to another depends on the complexity of the problem. For instance, the number of iterations required to train the Forward ANN models in this study was found to be in the range between 10 and 20 thousands, whereas, the number of iterations required to train the Inverse ANN-1 (project design) models was less than 500 epochs. Furthermore, it is essential to control and validate the efficiency of the training process by monitoring the validation error and performance graph while the network is being trained, to prevent any potential memorization problem, as described in Chapter 2.

- **Scaling the data and functional links:** it is important to scale the input and output data between the range of 1 and -1 before training the network. Despite the fact that the applied transfer function can perform this task, it was found that better results are achieved when these input and output data are scaled manually prior to training the data set. For instance, large output and input data, such as oil rate and fracture permeability, can be mathematically scaled by taking the logarithm of these data or dividing them by a large number. In this study, it was found that taking the logarithm of the input and output data prior to assign them to training gives more effective results compared to unscaled data set. As discussed in Chapter 2, functional links are another important aspect that can be added to improve the efficiency of the network. Functional links are mathematical relations between the input and output data that can be used to enhance the training performance of the network by adding additional useful nodes to the network. Several functional links were used for all proxy models and are highlighted in details in the next sections.
- **Error analysis**: after training the data, the performance and efficiency of the network is assessed by comparing the output result from the network for a given data point to the original corresponding target value from the numerical simulator. The data set allocated for testing could be used as a caliber to evaluate the prediction’s efficiency of the network for cases outside the training set. Hence, the absolute error between the network’s output, ANN value, and the simulator’s original value, simulator’s value, is calculated for each data point in the testing data set as follows:

\[ Error \% = \left| \frac{Value_{Simulator} - Value_{ANN}}{Value_{Simulator}} \right| \times 100 \]

As discussed previously, CMG STARS thermal commercial simulator was used to generate simulation results in this study. Furthermore, the average error per testing case can be used as a performance indicator of the network efficiency and is calculated as follows:

\[ Average \ Error \% = \frac{\sum_{i=1}^{N} Error \%}{N} \]

Where, \( N \) represents the total number of data points per testing case. For example, there are 68 data points per testing case for oil rate production data, hence \( N \) is equal to 68. Additionally, the arithmetic average of these average errors can be calculated to find the mean error for a given property in the network.

### 5.2 ANN Development for Water flooding Case

This section presents a detailed analysis of the ANN development of all three proxy models, Forward ANN, Inverse ANN-1 and Inverse ANN-2 for the water flooding case. Table 4-1 and Table 4-5 that were presented in Chapter 3 indicate the range of reservoir properties and design
parameters used to generate the data set for the water flooding case. Only water was used as an injection fluid to generate simulation results and hence the polymer and cross linker have zero concentrations in all cases. The data set contains 738 cases and was divided into 90% training, 5% validation and 5% testing. The next sections discuss in details the optimum ANN structure and analysis of collected results for all developed models for this water flooding case.

5.2.1 Forward ANN Model

The Forward ANN model was developed to predict and generate production profiles of oil rate, water cut and recovery factor for a given specified set of reservoir properties and design parameters. As opposed to polymer gel flooding, production profiles of water flooding indicate a unique signature of pre-mature water breakthrough during early production causing a significant drop in oil rate and ultimately low reservoir’s recovery, as can be clearly seen in the production plots presented later in the results’ section. The optimum network’s topography and analysis of Forward ANN results are discussed in details in the next sections.

5.2.1.1 ANN Structure

The network contains 738 cases and it was divided into 90% training, 5% validation and 5% for testing. The data set was trained using scaled conjugate gradient (trainscg) training function and log-sigmoid function was used as a transfer function (logsig). The optimum network structure for this model has a total of five hidden layers. The distribution of the neurons in these layers is 55, 65, 69, 75 and 64, summing up to a total of 328 neurons. The input layer contains 25 neurons, 14 of which are functional links between the reservoir properties and design parameters in the input layer. The output layer contains 204 neurons, each 68 neurons belong to oil rate, water cut and
recovery factor, representing a total time frequency of 68 data points collected over a 10-year period for each production performance indicator. Table 5-1 illustrates the ANN structure used to build this model.

Additionally, Table 5-2 summarizes the input and output components and the functional links used in this model. As discussed in section 5.1, the majority of the input data, except for the porosity, and all of the output data were scaled prior to training by taking the logarithmic value of each node, to improve the network’s performance and efficiency. In addition, it was observed that the injection rate is the most sensitive parameter in the model and hence was included in most functional links operations, refer to Table 5-2.

Table 5-1: Forward ANN model structure for water flooding case

<table>
<thead>
<tr>
<th>Layer</th>
<th>Neurons</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input (Reservoir + Design)</td>
<td>11</td>
</tr>
<tr>
<td>Input (Functional Links)</td>
<td>14</td>
</tr>
<tr>
<td>Hidden Layer 1</td>
<td>55</td>
</tr>
<tr>
<td>Hidden Layer 2</td>
<td>65</td>
</tr>
<tr>
<td>Hidden Layer 3</td>
<td>69</td>
</tr>
<tr>
<td>Hidden Layer 4</td>
<td>75</td>
</tr>
<tr>
<td>Hidden Layer 5</td>
<td>64</td>
</tr>
<tr>
<td>Output (Production Profiles)</td>
<td>204</td>
</tr>
</tbody>
</table>
Table 5-2: Input, output and functional links components of Forward ANN model (water flooding)

<table>
<thead>
<tr>
<th>INPUT</th>
<th>OUTPUT</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Reservoir Properties</strong></td>
<td><strong>Oil rate, water cut and recovery factor</strong></td>
</tr>
<tr>
<td>Reservoir Thickness</td>
<td>68 data points for each; time frequency as follows:</td>
</tr>
<tr>
<td>Matrix Porosity</td>
<td>15 days for year 1, 30 days for year 2, 90 days for year 3-10</td>
</tr>
<tr>
<td>Fracture Porosity</td>
<td></td>
</tr>
<tr>
<td>Matrix Permeability (Horizontal)</td>
<td></td>
</tr>
<tr>
<td>Matrix Permeability (Vertical)</td>
<td></td>
</tr>
<tr>
<td>Fracture Permeability</td>
<td></td>
</tr>
<tr>
<td>Fracture Spacing</td>
<td></td>
</tr>
<tr>
<td>Initial Water Saturation</td>
<td></td>
</tr>
<tr>
<td><strong>Design Parameters</strong></td>
<td></td>
</tr>
<tr>
<td>Injection Rate</td>
<td></td>
</tr>
<tr>
<td>Producer BHP</td>
<td></td>
</tr>
<tr>
<td>Drainage Area</td>
<td></td>
</tr>
<tr>
<td><strong>Functional Links</strong></td>
<td></td>
</tr>
<tr>
<td>(Injection Rate/Matrix Permeability )/100</td>
<td></td>
</tr>
<tr>
<td>$\log((\text{injection Rate})^{0.5}+(\text{Matrix Permeability})^{0.5})/10$</td>
<td></td>
</tr>
<tr>
<td>(Fracture Permeability/ Injection Rate)/10</td>
<td></td>
</tr>
<tr>
<td>$\log((\text{injection Rate})^{0.5}+(\text{Fracture Permeability})^{0.5})/10$</td>
<td></td>
</tr>
<tr>
<td>Drainage Area/Injection Rate</td>
<td></td>
</tr>
<tr>
<td>Fracture Spacing/Injection Rate</td>
<td></td>
</tr>
<tr>
<td>$\log((\text{Injection Rate})^{0.5}*(\text{Matrix Porosity})^{100}$</td>
<td></td>
</tr>
<tr>
<td>$\log((\text{Injection Rate})^{0.5}*(\text{Fracture Porosity})^{1000}$</td>
<td></td>
</tr>
<tr>
<td>$\log((\text{Injection Rate})^{0.5}*(\text{Producer BHP})$</td>
<td></td>
</tr>
<tr>
<td>$\log((\text{Injection Rate})^{0.5}/\text{Thickness})$</td>
<td></td>
</tr>
<tr>
<td>$\log((\text{Injection Rate})^{0.5}/\text{Water Saturation})$</td>
<td></td>
</tr>
<tr>
<td>$\log((\text{Thickness})^{0.5}*(\text{Drainage Area})$</td>
<td></td>
</tr>
<tr>
<td>$\log((\text{injection Rate})^{0.5}+(\text{Thickness})^{0.5}$</td>
<td></td>
</tr>
<tr>
<td>$\log((\text{injection Rate})^{0.5}+(\text{Drainage Area})^{0.5}$</td>
<td></td>
</tr>
</tbody>
</table>
5.2.1.2 Results and Error Analysis

The target tolerance for this forward problem was to obtain an average error per testing case of 10%. In general, matching the oil rate profiles was more difficult than matching both the water cut and recovery factor profiles for all cases. This is due to the fact that oil rate profiles vary widely from one case to another and could have a wider spectrum of data compared to the water cut and recovery factor profiles which are both more concentrated and have narrower range of data. For instance, the oil rate could vary from 100 to 2000 barrels per day, compared to the water cut which have a range of 0 to 100% only. Consequently, the oil rate produced the highest error between the three profiles.

It is important before presenting the forward results obtained for the optimum ANN structure displayed in Table 5-1, to compare the results acquired from different ANN structures. This comparison shall serve as a benchmark to demonstrate the process of selecting an optimum ANN structure for a given problem or model. Similar approach and method of investigation was adapted throughout this research to build the remaining ANN models. Generally, it was observed that increasing the number of hidden layers in this Forward ANN model generates better results and produces less error, compared to ANN structures with less number of layers. Table 5-3 and Figure 5-1 indicate that the mean error per testing case for oil rate, water cut and recovery factor decreases with increasing the number of hidden layers in the network. In addition, Table 5-4 and Figure 5-2 demonstrate the effect of increasing the number of layers in significantly reducing the oil rate error, showing the minimum, mean and maximum error obtained per ANN structure. Moreover, it was realized that to achieve a reasonable result per structure, the total number of neurons in all hidden layers should be at least 300 in this Forward ANN model. It was also observed that networks that contain less layers with large number of neurons usually take longer time to train.
than networks with more layers but less number of neurons per layer. For instance, the network with one hidden layer in Table 5-3 takes longer time to train than the three or five layers’ networks.

Table 5-3: Mean error comparison for different ANN structures

<table>
<thead>
<tr>
<th># of Hidden Layers</th>
<th>Neurons Distribution</th>
<th>Mean Error %</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Recovery Factor</td>
</tr>
<tr>
<td>1 layer</td>
<td>350</td>
<td>4.79</td>
</tr>
<tr>
<td>3 layers</td>
<td>100,150,100</td>
<td>3.62</td>
</tr>
<tr>
<td>5 layers (Optimum)</td>
<td>55,65,69,75,64</td>
<td>2.5</td>
</tr>
</tbody>
</table>

Figure 5-1: Mean error comparison for different ANN structures

Table 5-4: Oil rate's error comparison for different ANN structures

<table>
<thead>
<tr>
<th># of Hidden Layers</th>
<th>Neurons Distribution</th>
<th>Oil Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Min Error %</td>
</tr>
<tr>
<td>1 layer</td>
<td>350</td>
<td>3.14</td>
</tr>
<tr>
<td>3 layers</td>
<td>100,150,100</td>
<td>2.29</td>
</tr>
<tr>
<td>5 layers (Optimum)</td>
<td>55,65,69,75,64</td>
<td>2.51</td>
</tr>
</tbody>
</table>
Figure 5-2: Comparison of oil rate’s error per structure

Figure 5-3, Figure 5-4 and Figure 5-5 show the mean error distribution per testing case for recovery factor, oil rate and water cut, respectively, for the optimum ANN structure displayed in Table 5-1. This structure has generated production profiles that matched the original profiles from the numerical simulator with an average error of only 2.5%, 5.63% and 1.32% for recovery factor, oil rate and water cut, respectively. Of the 37 testing cases, Figures 5-6 to 5-14 show examples of the various production trends matched and generated by the ANN, in comparison to the profiles produced originally by the simulator. Collectively, these trends clearly show the signature of premature water breakthrough at early production time due to the presence of very high conductive fractures in the water flooding model.
Figure 5-3: Mean error distribution for recovery factor (water flooding case)

Figure 5-4: Mean error distribution for oil rate (water flooding case)
Figure 5-5: Mean error distribution for water cut (water flooding case)

Figure 5-6: Comparison of water flooding production profiles generated by ANN and numerical simulator (Case-30)
Figure 5-7: Comparison of water flooding production profiles generated by ANN and numerical simulator (Case-70)

Figure 5-8: Comparison of water flooding production profiles generated by ANN and numerical simulator (Case-118)
Figure 5-9: Comparison of water flooding production profiles generated by ANN and numerical simulator (Case-122)

Figure 5-10: Comparison of water flooding production profiles generated by ANN and numerical simulator (Case-138)
Figure 5-11: Comparison of water flooding production profiles generated by ANN and numerical simulator (Case-147)

Figure 5-12: Comparison of water flooding production profiles generated by ANN and numerical simulator (Case-245)
Figure 5-13: Comparison of water flooding production profiles generated by ANN and numerical simulator (Case-354)

Figure 5-14: Comparison of water flooding production profiles generated by ANN and numerical simulator (Case-474)
5.2.2 Inverse ANN-1 Model

The Inverse ANN-1 model is an inverse-looking network that estimates the project’s design parameters required to generate a given production profile for a given set of reservoir properties. For water flooding model, three design parameters are used: injection rate, producer’s operating bottom-hole pressure and drainage area. As explained in Chapter 4, these are designed to reflect the orientation of a five-spot pattern, which is most commonly used to design secondary and tertiary recovery projects. The optimum network’s topography and analysis of the Inverse ANN-1’s results are discussed in details in the next sections.

5.2.2.1 ANN Structure

A total of 738 cases were fed into the network and divided into 90% training, 5% validation and 5% for testing. The data set was trained using scaled conjugate gradient (trainscg) training function and log-sigmoid function was used as a transfer function (logsig). The optimum network structure for this model has a single hidden layer containing 7 neurons. The input layer contains a total of 214 neurons; 8 of which are input of reservoir properties whereas 204 neurons belong to production input data of oil rate, water cut and recovery factor, containing 68 data points for each performance indicator. In addition, 2 more neurons in the input layer are functional links between the fracture and matrix porosity and permeability. On the other hand, the output layer contains 5 neurons, 3 of which are to estimate the project’s design parameters of injection rate, producer flowing bottom-hole pressure and drainage area, whereas 2 neurons are functional links in the output layer. Table 5-5 illustrates the ANN structure used to build this model. Furthermore, Table 5-6 lists all the input and output components and the functional links used in this model.
Table 5-5: Inverse ANN-1 model's structure for water flooding case

<table>
<thead>
<tr>
<th>Layer</th>
<th>Neurons</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input (Reservoir Properties)</td>
<td>8</td>
</tr>
<tr>
<td>Input (Production Profiles)</td>
<td>204</td>
</tr>
<tr>
<td>Input (Functional Links)</td>
<td>2</td>
</tr>
<tr>
<td>Hidden Layer 1</td>
<td>7</td>
</tr>
<tr>
<td>Output (Design Parameters)</td>
<td>3</td>
</tr>
<tr>
<td>Output (Functional Links)</td>
<td>2</td>
</tr>
</tbody>
</table>

Table 5-6: Input, output and functional link's components for Inverse ANN-1 (water flooding)

<table>
<thead>
<tr>
<th>INPUT</th>
<th>Reservoir Properties</th>
</tr>
</thead>
</table>
|                            | Reservoir Thickness  
|                            | Matrix Porosity  
|                            | Fracture Porosity  
|                            | Matrix Permeability (Horizontal)  
|                            | Matrix Permeability (Vertical)  
|                            | Fracture Permeability  
|                            | Fracture Spacing  
|                            | Initial Water Saturation  |
| Production Profiles        | 68 data points for each; time frequency as follows:  
| Oil rate, water cut &       | 15 days for year 1, 30 days for year 2, 90 days for year 3-10  
| recovery factor            |  
| Functional Links           | Fracture Porosity/Matrix Porosity  
|                            | log[Fracture Permeability/Matrix Permeability]  |

<table>
<thead>
<tr>
<th>OUTPUT</th>
<th>Design Parameters</th>
</tr>
</thead>
</table>
|                            | Injection Rate  
|                            | Producer BHP  
|                            | Drainage Area  |
| Functional Links           | log[Injection Rate/Producer BHP]  
|                            | log[Injection Rate/Drainage Area]  |

5.2.2.2 Results and Error Analysis

For this inverse problem, it was observed that only one single hidden layer with 7 neurons is required for the network to achieve a reasonable match for the design parameters. Unlike the
Forward ANN model, this indicates that the solution to this inverse problem is less complex and more linear due to the fact that there is enough diverse input data in this model that the network can use to correlate to the output layer using only one hidden layer. The optimum ANN structure displayed in Table 5-5 resulted in an overall mean error of only 7.06% and a maximum error of 16.2% for all 37 testing cases, refer to Figure 5-15 showing the average error distribution per case for all three design parameters. Moreover, Figure 5-16 shows the average error obtained per design parameter in this model. As can be seen from Figure 5-16, the mean error distribution per parameter is: 10.8%, 5.3% and 5.0%, for injection rate, producer Bottom-Hole Pressure (BHP) and drainage area, respectively. In addition, Figure 5-17, Figure 5-18 and Figure 5-19 show a comparison of the results predicted by the network compared to the original values from the simulator per each testing case for each design parameter. Please note that the results displayed in Figure 5-19 are affected by the narrow scale, thus, the comparison might not be very obvious. Nonetheless, Figure 5-20 shows the error distribution per case obtained for the producer BHP, indicating a maximum offset error of less than 15% compared to the original values obtained from the simulator.
Figure 5-15: Mean error distribution per case (design water flooding)

Figure 5-16: Mean error distribution per design parameter (water flooding)
Figure 5-17: Comparison of injection rate predicted by ANN and simulator (water flooding)

Figure 5-18: Comparison of drainage area predicted by ANN and simulator (water flooding)
Figure 5-19: Comparison of producer BHP predicted by ANN and simulator (water flooding)

Figure 5-20: Error distribution for producer BHP per case (water flooding)
5.2.3 Inverse ANN-2 Model

The Inverse ANN-2 model is an inverse-looking network that estimates the various reservoir properties associated with a given production profile and project’s design parameters. Hence, this model could be used as a tool for history matching of the field’s production profiles by estimating the associated reservoir parameters. A total of seven reservoir properties are captured in this model, including: matrix and fracture porosity, matrix and fracture permeability, fracture spacing, reservoir thickness and initial water saturation. The optimum network’s topography and analysis of the Inverse ANN-2’s results are discussed in details in the next sections.

5.2.3.1 ANN Structure

The network contains 738 cases and it was divided into 90% training, 5% validation and 5% for testing. The data set was trained using scaled conjugate gradient (trainscg) training function and log-sigmoid function was used as a transfer function (logsig). Table 5-7 below describes the ANN structure used to build this model.

<table>
<thead>
<tr>
<th>Layer</th>
<th>Neurons</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input (Design Parameters)</td>
<td>3</td>
</tr>
<tr>
<td>Input (Production Profiles)</td>
<td>204</td>
</tr>
<tr>
<td>Input (Functional Links)</td>
<td>5</td>
</tr>
<tr>
<td>Hidden Layer 1</td>
<td>10</td>
</tr>
<tr>
<td>Hidden Layer 2</td>
<td>28</td>
</tr>
<tr>
<td>Hidden Layer 3</td>
<td>20</td>
</tr>
<tr>
<td>Hidden Layer 4</td>
<td>20</td>
</tr>
<tr>
<td>Hidden Layer 5</td>
<td>16</td>
</tr>
<tr>
<td>Hidden Layer 6</td>
<td>17</td>
</tr>
<tr>
<td>Output (Reservoir Properties)</td>
<td>7</td>
</tr>
<tr>
<td>Output (Functional Links)</td>
<td>13</td>
</tr>
</tbody>
</table>
As can be seen from Table 5-7, the optimum network structure for this model has a total of six hidden layers. The distribution of the neurons in these layers is 10, 28, 20, 20, 16 and 7, summing up to a total of 111 neurons. The input layer contains a total of 212 neurons; 3 of which are input of design parameters, whereas 204 neurons belong to production input data of oil rate, water cut and recovery factor, containing 68 data points for each performance indicator. In addition, 5 neurons in the input layer are functional links, mainly relating the sensitive injection rate’s parameter to other input properties. The output layer contains 20 neurons, 7 of which are to estimate the various reservoir properties associated with this model, whereas 13 additional neurons are included as functional links in the output layer. Table 5-8 below lists all the input and output components and the functional links used in this model.
**Table 5-8: Inputs, outputs and functional links’ components for Inverse ANN-2 (water flooding)**

<table>
<thead>
<tr>
<th>INPUT</th>
<th>Design Parameters</th>
<th>Injection Rate</th>
<th>Producer BHP</th>
<th>Drainage Area</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Production Profiles</strong></td>
<td>Oil rate, water cut &amp; recovery factor</td>
<td>68 data points for each; time frequency as follows:</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>15 days for year 1, 30 days for year 2, 90 days for year 3-10</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Functional Links</td>
<td>log[Drainage Area/Injection Rate]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>log[Injection Rate/Producer BHP]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>log[Injection Rate/Initial Oil Rate]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>log[(Injection Rate)^0.5 + (Drainage Area)^0.5]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>log[(Injection Rate)^0.5 + (Producer BHP)^0.5]</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>OUTPUT</th>
<th>Reservoir Properties</th>
<th>Reservoir Thickness</th>
<th>Matrix Porosity</th>
<th>Fracture Porosity</th>
<th>Matrix Permeability</th>
<th>Fracture Permeability</th>
<th>Fracture Spacing</th>
<th>Initial Water Saturation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Functional Links</td>
<td>log[Fracture Spacing /Matrix Porosity]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>log[Fracture Porosity/Matrix Porosity]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>log[Matrix Permeability/Matrix Porosity]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>log[Fracture Permeability/Matrix Porosity]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>log[Water Saturation/Matrix Porosity]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>log[Reservoir Thickness/Matrix Porosity]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>log[(Injection Rate)^0.5 + (Fracture Spacing)^0.5]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>log[(Injection Rate)^0.5 + (Fracture Porosity)^0.5]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>log[(Injection Rate)^0.5 + (Matrix Permeability)^0.5]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>log[(Injection Rate)^0.5 + (Fracture Permeability)^0.5]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>log[(Injection Rate)^0.5 + (Water Saturation)^0.5]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>log[(Injection Rate)^0.5 + (Reservoir Thickness)^0.5]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(Matrix Porosity)^0.5 + (Fracture Porosity)^0.5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

5.2.3.2 Results and Error Analysis

For this inverse problem, it was observed that increasing the number of hidden layers in the network would significantly improve the results and produce a better match for the reservoir properties. For instance, Figure 5-21 and Figure 5-22 compares the error distribution per testing case for all reservoir properties obtained for the optimum 6-layers ANN structure displayed in Table 5-7 and another ANN structure with only 3 hidden layers, with neurons’ distribution of 50, 35 and 20. Comparing Figure 5-22 with Figure 5-21 (note they have the same y-scale), the overall error distribution and mean error was considerably reduced from 46.5% to 18.1%, illustrating the effect of adding extra 3 hidden layers in the model.

![Error Distribution Per Case](image)

Figure 5-21: Mean error distribution per case for Inverse ANN-2 (3 layers-water flooding)
Moreover, Figure 5-23 shows the average error obtained per reservoir property in this model. As can be seen from Figure 5-23, the mean error per property ranges between 8 and 28%. In addition, Figure 5-24, Figure 5-25, Figure 5-26, Figure 5-27, Figure 5-28, Figure 5-29 and Figure 5-30 show a comparison of the results predicted by the network compared to the original values from the simulator per each testing case for each reservoir property in the model. As can be seen from these plots, the fracture porosity produced the highest error compared to other properties. This is largely attributed to the fact that the fracture porosity data are very small, i.e. in the order of $10^{-4}$ to $10^{-2}$, such that an order of magnitude deviation from the original value would produce a high percentage of error. Nonetheless, both the simulator and ANN model proved to be insensitive to the change in fracture porosity compared to other properties. For instance, Figure 5-31 compares the difference in the generated production profiles using the Forward ANN tool between the actual fracture porosity and the one predicted by Inverse ANN-2 model for Case-14. The difference
between these two profiles is negligible despite the huge difference between the two fracture porosities.

Figure 5-23: Mean error distribution per reservoir property (water flooding)
Figure 5-24: Comparison of matrix porosity predicted by ANN and simulator (water flooding)

Figure 5-25: Comparison of fracture porosity predicted by ANN and simulator (water flooding)
Figure 5-26: Comparison of matrix permeability predicted by ANN and simulator (water flooding)

Figure 5-27: Comparison of fracture permeability predicted by ANN and simulator (water flooding)
Figure 5-28: Comparison of reservoir thickness predicted by ANN and simulator (water flooding)

Figure 5-29: Comparison of water saturation predicted by ANN and simulator (water flooding)
Figure 5-30: Comparison of fracture spacing predicted by ANN and simulator (water flooding)

Figure 5-31: Effect of fracture porosity (pof) on production profiles (water flooding)
5.3 ANN Development for Polymer Gel Flooding Case

This section presents an in-depth analysis of the ANN development of all three proxy models, Forward ANN, Inverse ANN-1 and Inverse ANN-2 for the polymer gel flooding case. Table 4-1 and Table 4-5 that were presented in Chapter 3 indicate the range of reservoir properties and design parameters used to generate the data set for the polymer gel flooding case. For this case, soluble concentrations of polymer and cross linker are both injected with water to form an in-situ gel that is capable of plugging the fractures and preventing early water breakthrough in the model. Consequently, production profiles generated from this case indicate a significant improvement in sweep efficiency and oil recovery compared to the water flooding scenario. A total of 1000 cases were generated for this case and fed into the neural network. Similar to the water flooding scenario, the data set was divided into 90% training, 5% validation and 5% testing. The next sections discuss in details the optimum ANN structure and analysis of collected results for all developed models for this polymer gel flooding case.

5.3.1 Forward ANN Model

The Forward ANN model is developed to predict and generate production profiles of oil rate, water cut and recovery factor for a given specified set of reservoir properties and design parameters. The generated production profiles for the polymer gel flooding scenario indicate a significant improvement in oil recovery compared to the production profiles of water flooding. This improvement is largely attributed to the fact that the injected gel plugs the conductive fractures and delays water breakthrough into the producer, consequently, improving overall sweep efficiency and oil recovery from the reservoir’s matrix. The optimum network’s topography and analysis of Forward ANN results and production profiles are discussed in details in the next sections.
5.3.1.1 ANN Structure

The network contains 1000 cases and it was divided into 90% training, 5% validation and 5% for testing. The data set was trained using scaled conjugate gradient (trainscg) training function and log-sigmoid function was used as a transfer function (logsig). The optimum network structure for this model has a total of six hidden layers. The distribution of the neurons in these layers is 90, 95, 110, 150, 110 and 115, summing up to a total of 670 neurons. The input layer contains 29 neurons, 16 of which are functional links between the reservoir properties and design parameters in the input layer. The output layer contains 204 neurons, each 68 neurons belong to oil rate, water cut and recovery factor, representing a total time frequency of 68 data points collected over a 10-year period for each production performance indicator. Table 5-9 illustrates the ANN structure used to build this model.

Moreover, Table 5-10 lists the input, output and the functional links components used in this model. As previously mentioned, input and output data were scaled by taking the logarithm for each node, prior to training to improve the results. Similarly, the injection rate was observed to be the most sensitive parameter, and hence was used in most functional links’ operations, refer to Table 5-10.

Table 5-9: Forward ANN’s model structure for polymer gel case

<table>
<thead>
<tr>
<th>Layer</th>
<th>Neurons</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input (Reservoir + Design)</td>
<td>13</td>
</tr>
<tr>
<td>Input (Functional Links)</td>
<td>16</td>
</tr>
<tr>
<td>Hidden Layer 1</td>
<td>90</td>
</tr>
<tr>
<td>Hidden Layer 2</td>
<td>95</td>
</tr>
<tr>
<td>Hidden Layer 3</td>
<td>110</td>
</tr>
<tr>
<td>Hidden Layer 4</td>
<td>150</td>
</tr>
<tr>
<td>Hidden Layer 5</td>
<td>110</td>
</tr>
<tr>
<td>Hidden Layer 6</td>
<td>115</td>
</tr>
<tr>
<td>Output (Production Profiles)</td>
<td>204</td>
</tr>
</tbody>
</table>
Table 5-10: Inputs, outputs and functional links components for Forward ANN (polymer gel)

<table>
<thead>
<tr>
<th>INPUT</th>
<th>Reservoir Properties</th>
<th>Design Parameters</th>
<th>Functional Links</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Reservoir Thickness</td>
<td>Injection Rate</td>
<td>(Injection Rate/Matrix Permeability )/100</td>
</tr>
<tr>
<td></td>
<td>Matrix Porosity</td>
<td>Producer BHP</td>
<td>log[(injection Rate)(^{0.5}) + (Matrix Permeability)(^{0.5})]/10</td>
</tr>
<tr>
<td></td>
<td>Fracture Porosity</td>
<td>Drainage Area</td>
<td>(Fracture Permeability / Injection Rate)/10</td>
</tr>
<tr>
<td></td>
<td>Matrix Permeability (H)</td>
<td></td>
<td>log[(injection Rate)(^{0.5}) + (Fracture Permeability)(^{0.5})]/10</td>
</tr>
<tr>
<td></td>
<td>Matrix Permeability (V)</td>
<td></td>
<td>Drainage Area/Injection Rate</td>
</tr>
<tr>
<td></td>
<td>Fracture Permeability</td>
<td>Fracture Spacing/Injection Rate</td>
<td>log[Matrix Porosity/Injection Rate]*100</td>
</tr>
<tr>
<td></td>
<td>Fracture Spacing</td>
<td></td>
<td>log[Fracture Porosity/Injection Rate]*1000</td>
</tr>
<tr>
<td></td>
<td>Initial Water Saturation</td>
<td></td>
<td>log[Injection Rate/Producer BHP]</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>log[Injection Rate/Thickness]</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>log[Injection Rate/Water Saturation]</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>log[Thickness * Drainage Area]</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>log[(injection Rate)(^{0.5}) + (Thickness)(^{0.5})]</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>log[(injection Rate)(^{0.5}) + (Drainage Area)(^{0.5})]</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>log[Polymer Concent. + XLinker Concent.]/10</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>log [(injection Rate)(^{0.5}) + (Polymer + Xlinker Concent.)(^{0.5})]</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>OUTPUT</th>
<th>Oil rate, water cut and recovery factor</th>
<th>68 data points for each; time frequency as follows:</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>15 days for year 1, 30 days for year 2, 90 days for year 3-10</td>
</tr>
</tbody>
</table>
5.3.1.2 Results and Error Analysis

At first, it was difficult to match all production trends in this forward problem. As opposed to water flooding, the addition of polymer gels into the model improves production profiles by arresting early water breakthrough and sustaining higher plateau oil rate during the first 20 to 40 months of production. Therefore, a clear signature of discontinuity appears in these production curves at the time of water breakthrough, especially for oil rate and water cut profiles, as can be seen in Figures 5-35 to 5-50. The most significant factor that helped improving the results in this model was to ensure that the data set contains a sufficient number of cases that cover all possible scenarios and production trends. Consequently, the optimum number of data set found for this problem was 1000 cases. Furthermore, similar to the previous forward problem for water flooding case, it was found that increasing the number of hidden layers in the network considerably improves results. In fact, due to the complexity of production trends in this scenario, it was realized that in order to achieve reasonable matching results for this problem, the network’s structure should contain at least six hidden layers with almost double the total number of neurons that was required for the water flooding scenario. Table 5-9 shows the optimum ANN structure used for this Forward ANN model, as was described in the previous section.

Figure 5-32, Figure 5-33 and Figure 5-34 indicate the mean error distribution per testing case for recovery factor, oil rate and water cut, respectively obtained for this Forward ANN model. The optimum ANN structure displayed in Table 5-9, has generated production profiles that matched the original profiles from the numerical simulator with an average error of 2.46%, 10.31% and 8.01% for recovery factor, oil rate and water cut, respectively. As can be seen from these distributions, the maximum error obtained was less than 25% for all cases. Of the 50 testing cases, Figures 5-35 to 5-50 show examples of the various production trends matched and generated by the ANN, in comparison to the profiles produced originally by the simulator. Generally, original
production trends obtained from the simulator for this polymer gel scenario, indicate a unique signature of production curve’s discontinuity in which a sharp increase in water cut and decline in oil rate occurs abruptly at the time of water breakthrough. Generally, the highest matching errors were associated with this discontinuous region, as the neural network is not capable of producing a sharp discontinuous curve similar to the simulator.

Figure 5-32: Mean error distribution for recovery factor (polymer gel)
Figure 5-33: Mean error distribution for oil rate (polymer gel)

Figure 5-34: Mean error distribution for water cut (polymer gel)
Figure 5-35: Comparison of polymer gel profiles generated by ANN & simulator (Case-38)

Figure 5-36: Comparison of polymer gel profiles generated by ANN & simulator (Case-42)
Figure 5-37: Comparison of polymer gel profiles generated by ANN & simulator (Case-53)

Figure 5-38: Comparison of polymer gel profiles generated by ANN & simulator (Case-113)
Figure 5-39: Comparison of polymer gel profiles generated by ANN & simulator (Case-195)

Figure 5-40: Comparison of polymer gel profiles generated by ANN & simulator (Case-227)
Figure 5-41: Comparison of polymer gel profiles generated by ANN & simulator (Case-248)

Figure 5-42: Comparison of polymer gel profiles generated by ANN & simulator (Case-363)
Figure 5-43: Comparison of polymer gel profiles generated by ANN & simulator (Case-456)

Figure 5-44: Comparison of polymer gel profiles generated by ANN & simulator (Case-472)
Figure 5-45: Comparison of polymer gel profiles generated by ANN & simulator (Case-589)

Figure 5-46: Comparison of polymer gel profiles generated by ANN & simulator (Case-662)
Figure 5-47: Comparison of polymer gel profiles generated by ANN & simulator (Case-675)

Figure 5-48: Comparison of polymer gel profiles generated by ANN & simulator (Case-733)
Figure 5-49: Comparison of polymer gel profiles generated by ANN & simulator (Case-801)

Figure 5-50: Comparison of polymer gel profiles generated by ANN & simulator (Case-918)
5.3.2 Inverse ANN-1 Model

The Inverse ANN-1 model is an inverse-looking network that estimates the project’s design parameters required to generate a given production profile for a given set of reservoir properties. For the polymer gel flooding scenario, five design parameters are considered, including: injection rate, producer’s operating bottom-hole pressure, drainage area, polymer concentration and cross linker concentration. As explained in Chapter 4, these are designed to reflect the orientation of a five-spot pattern, which is most commonly used to design secondary and tertiary recovery projects. The optimum network’s topography and analysis of the Inverse ANN-1’s results are discussed in details in the next sections.

5.3.2.1 ANN Structure

A total of 1000 cases were fed into the network and divided into 90% training, 5% validation and 5% for testing. The data set was trained using scaled conjugate gradient (trainscg) training function and log-sigmoid function was used as a transfer function (logsig).

The optimum network structure for this model has a single hidden layer containing 9 neurons. The input layer contains a total of 215 neurons; 8 of which are input of reservoir properties whereas 204 neurons belong to production input data of oil rate, water cut and recovery factor, containing 68 data points for each performance indicator. In addition, 3 more neurons are functional links between the reservoir properties in the input layer. On the other hand, the output layer contains 11 neurons, 5 of which are to estimate the project’s design parameters of injection rate, producer flowing bottom-hole pressure, drainage area, polymer and cross linker concentrations, whereas 6 neurons are functional links in the output layer. Table 5-11 illustrates the ANN structure used to
build this model. Furthermore, Table 5-12 summarizes all the input and output components and the functional links used in this model.

Table 5-11: Inverse ANN-1 model’s structure for polymer gel case

<table>
<thead>
<tr>
<th>Layer</th>
<th>Neurons</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input (Reservoir Properties)</td>
<td>8</td>
</tr>
<tr>
<td>Input (Production Profiles)</td>
<td>204</td>
</tr>
<tr>
<td>Input (Functional Links)</td>
<td>3</td>
</tr>
<tr>
<td>Hidden Layer 1</td>
<td>9</td>
</tr>
<tr>
<td>Output (Design Parameters)</td>
<td>5</td>
</tr>
<tr>
<td>Output (Functional Links)</td>
<td>6</td>
</tr>
</tbody>
</table>
Table 5-12: Inputs, outputs and functional links components for Inverse ANN-1 (polymer gel)

<table>
<thead>
<tr>
<th>INPUT</th>
<th>Reservoir Properties</th>
<th>Output</th>
<th>Design Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Reservoir Thickness</td>
<td></td>
<td>Injection Rate</td>
</tr>
<tr>
<td></td>
<td>Matrix Porosity</td>
<td></td>
<td>Producer BHP</td>
</tr>
<tr>
<td></td>
<td>Fracture Porosity</td>
<td></td>
<td>Drainage Area</td>
</tr>
<tr>
<td></td>
<td>Matrix Permeability (Horizontal)</td>
<td></td>
<td>Polymer Concentration</td>
</tr>
<tr>
<td></td>
<td>Matrix Permeability (Vertical)</td>
<td></td>
<td>Cross linker Concentration</td>
</tr>
<tr>
<td></td>
<td>Fracture Permeability</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Fracture Spacing</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Initial Water Saturation</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Production Profiles</th>
<th>68 data points for each; time frequency as follows:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oil rate, water cut &amp; recovery factor</td>
<td>15 days for year 1, 30 days for year 2, 90 days for year 3-10</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Functional Links</th>
<th>Fracture Porosity/Matrix Porosity</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>log[Fracture Permeability/Matrix Permeability]</td>
</tr>
<tr>
<td></td>
<td>log[(Matrix Porosity)^0.5+(Matrix Permeability)^0.5]</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>OUTPUT</th>
<th>Design Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Injection Rate</td>
</tr>
<tr>
<td></td>
<td>Producer BHP</td>
</tr>
<tr>
<td></td>
<td>Drainage Area</td>
</tr>
<tr>
<td></td>
<td>Polymer Concentration</td>
</tr>
<tr>
<td></td>
<td>Cross linker Concentration</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Functional Links</th>
<th>log[(injection Rate)^0.5+(Drainage Area)^0.5]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>log[(injection Rate)^0.5+(Producer BHP)^0.5]</td>
</tr>
<tr>
<td></td>
<td>log[(injection Rate)^0.5+(Polymer Concentration)^0.5]</td>
</tr>
<tr>
<td></td>
<td>log[(injection Rate)^0.5+(Cross linker Concentration)^0.5]</td>
</tr>
<tr>
<td></td>
<td>log[(Producer BHP)^0.5+(Polymer Concentration)^0.5]</td>
</tr>
<tr>
<td></td>
<td>log[(Producer BHP)^0.5+(Cross linker Concentration)^0.5]</td>
</tr>
</tbody>
</table>

5.3.2.2 Results and Error Analysis

For this inverse problem, it was observed that only one single hidden layer with 9 neurons is required for the network to achieve a reasonable match for the design parameters. This is very similar to the structure used to solve the inverse design problem for the water flooding case.
Nonetheless, more functional links were added in the output layer to include the new design parameters, polymer and cross linker concentrations, refer to Table 5-12. The optimum ANN structure displayed in Table 5-11 resulted in an overall mean error of only 7.95% and a maximum error of 19.2% for all 50 testing cases, refer to Figure 5-51 showing the average error distribution per case for all five design parameters. Moreover, Figure 5-52 indicates the average error obtained per design parameter in this model. As can be seen from Figure 5-52, the mean error distribution per parameter is: 9.1%, 5.6%, 4.7%, 10.8% and 9.5% for injection rate, producer Bottom-Hole Pressure (BHP), drainage area, polymer and cross linker concentrations, respectively. In addition, Figure 5-53, Figure 5-54, Figure 5-55, Figure 5-56 and Figure 5-57 present a comparison of the results predicted by the network compared to the original values from the simulator per each testing case for each design parameter. Similar to the water flooding case, note that the results displayed in Figure 5-57 are affected by the narrow scale, thus, the comparison might not be very obvious. Nonetheless, Figure 5-58 demonstrates the error distribution per case obtained for the producer BHP, indicating a maximum offset error of less than 15% compared to the original values obtained from the simulator.
Figure 5-51: Mean error distribution per case (design-polymer gel)

Figure 5-52: Mean error distribution per design parameter (polymer gel)
Figure 5-53: Comparison of drainage area predicted by ANN and simulator (polymer gel)

Figure 5-54: Comparison of injection rate predicted by ANN and simulator (polymer gel)
Figure 5-55: Comparison of polymer concentration predicted by ANN and simulator (polymer gel)

Figure 5-56: Comparison of cross linker concentration predicted by ANN and simulator (polymer gel)
Figure 5-57: Comparison of producer BHP predicted by ANN and simulator (polymer gel)

Figure 5-58: Error distribution for producer BHP per case (polymer gel)
5.3.3 Inverse ANN-2 Model

The Inverse ANN-2 model is an inverse-looking network that estimates the various reservoir properties associated with a given production profile and project’s design parameters for the polymer gel flooding scenario. Hence, this model could be used as a tool for history matching of the field’s production profiles by estimating the associated reservoir parameters. A total of seven reservoir properties are captured in this model, including: matrix and fracture porosity, matrix and fracture permeability, fracture spacing, reservoir thickness and initial water saturation. The optimum network’s topography and analysis of the Inverse ANN-2’s results are discussed in details in the next sections.

5.3.3.1 ANN Structure

The network contains 1000 cases and it was divided into 90% training, 5% validation and 5% for testing. The data set was trained using scaled conjugate gradient (trainscg) training function and log-sigmoid function was used as a transfer function (logsig). Table 5-13 below describes the ANN structure used to build this model.

Table 5-13: Inverse ANN-2 model's structure for polymer gel case

<table>
<thead>
<tr>
<th>Layer</th>
<th>Neurons</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input (Design Parameters)</td>
<td>5</td>
</tr>
<tr>
<td>Input (Production Profiles)</td>
<td>204</td>
</tr>
<tr>
<td>Input (Functional Links)</td>
<td>9</td>
</tr>
<tr>
<td>Hidden Layer 1</td>
<td>55</td>
</tr>
<tr>
<td>Hidden Layer 2</td>
<td>75</td>
</tr>
<tr>
<td>Hidden Layer 3</td>
<td>68</td>
</tr>
<tr>
<td>Hidden Layer 4</td>
<td>60</td>
</tr>
<tr>
<td>Hidden Layer 5</td>
<td>65</td>
</tr>
<tr>
<td>Hidden Layer 6</td>
<td>64</td>
</tr>
<tr>
<td>Output (Reservoir Properties)</td>
<td>7</td>
</tr>
<tr>
<td>Output (Functional Links)</td>
<td>12</td>
</tr>
</tbody>
</table>
As can be seen from Table 5-13, the optimum network structure for this model has a total of six hidden layers. The distribution of the neurons in these layers is 55, 75, 68, 60, 65 and 64 summing up to a total of 387 neurons. The input layer contains a total of 218 neurons; 5 of which are input of design parameters whereas 204 neurons belong to production input data of oil rate, water cut and recovery factor, containing 68 data points for each performance indicator. In addition, 9 neurons in the input layer are functional links, mainly relating the sensitive injection rate’s parameter to other input properties. The output layer contains 19 neurons, 7 of which are to estimate the various reservoir properties associated with this model, whereas 12 additional neurons are included as functional links in the output layer. Table 5-14 below lists all the input and output components and the functional links used in this model.
<table>
<thead>
<tr>
<th>Input/Output Component</th>
<th>Design Parameters</th>
<th>Production Profiles</th>
<th>Functional Links</th>
<th>Reservoir Properties</th>
<th>Functional Links</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>INPUT</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Design Parameters</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Injection Rate</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Producer BHP</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Drainage Area</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Polymer Concentration</td>
<td></td>
<td></td>
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</tr>
<tr>
<td></td>
<td>Cross Linker Concentration</td>
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<tr>
<td></td>
<td><strong>Production Profiles</strong></td>
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<tr>
<td></td>
<td>Oil rate, water cut &amp; recovery factor</td>
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<td></td>
<td>68 data points for each; time frequency as follows:</td>
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<tr>
<td></td>
<td>15 days for year 1, 30 days for year 2, 90 days for year 3-10</td>
<td></td>
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<td></td>
</tr>
<tr>
<td><strong>Functional Links</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>log[Drainage Area/Injection Rate]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>log[Injection Rate/Producer BHP]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>log[Injection Rate/Initial Oil Rate]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>log[(Injection Rate)(^{0.5}) + (Drainage Area)(^{0.5})]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>log[(Injection Rate)(^{0.5}) + (Producer BHP)(^{0.5})]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>log[((Injection Rate)(^{0.5}) + (Polymer Concentration)(^{0.5})]</td>
<td></td>
<td></td>
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</tr>
<tr>
<td></td>
<td>log[(Injection Rate)(^{0.5}) + (Xlinker Concentration)(^{0.5})]</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td></td>
<td>log[(Producer BHP)(^{0.5}) + (Polymer Concentration)(^{0.5})]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>log[(Producer BHP)(^{0.5}) + (Xlinker Concentration)(^{0.5})]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>OUTPUT</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Functional Links</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>log[Fracture Spacing /Matrix Porosity]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>log[Fracture Porosity/Matrix Porosity]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>log[Matrix Permeability/Matrix Porosity]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>log[Fracture Permeability/Matrix Porosity]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>log[Water Saturation/Matrix Porosity]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>log[Reservoir Thickness/Matrix Porosity]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>log[(Injection Rate)(^{0.5}) + (Fracture Spacing)(^{0.5})]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>log[(Injection Rate)(^{0.5}) + (Fracture Porosity)(^{0.5})]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>log[(Injection Rate)(^{0.5}) + (Matrix Permeability)(^{0.5})]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>log[(Injection Rate)(^{0.5}) + (Fracture Permeability)(^{0.5})]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>log[(Injection Rate)(^{0.5}) + (Water Saturation)(^{0.5})]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(Matrix Porosity)(^{0.5}) + (Fracture Porosity)(^{0.5})</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
5.3.3.2 Results and Error Analysis

Similar to the water flooding case, it was realized that the optimum network structure for this inverse problem contains six hidden layers. However, due to the increase complexity of this polymer gel flooding case compared to the water flooding case, the number of neurons in each hidden layer has to be subsequently increased until a reasonable match for the reservoir properties was obtained for this proxy model. The final optimum ANN structure for this model was as described previously in Table 5-13. Figure 5-59 indicates the error distribution per testing case for all reservoir properties obtained for this optimum structure. As can be seen from Figure 5-59, the mean error distribution for these cases is 19.6%, with a maximum mean error of less than 50% per case. This large error was mainly attributed to the mismatch of fracture porosity. Nonetheless, as will be shown later on, the model is insensitive to the fracture porosity parameter and thus this mismatch does not necessarily affect the production or forward results, refer to Figure 5-68.

Moreover, Figure 5-60 shows the average error obtained per reservoir property in this model. As can be seen from Figure 5-60, the mean error per property ranges between 13 and 28%. In addition, Figure 5-61, Figure 5-62, Figure 5-63, Figure 5-64, Figure 5-65, Figure 5-66 and Figure 5-67 present a comparison of the results predicted by the network compared to the original values from the simulator per each testing case for each reservoir property in the model. As can be seen from these plots, the fracture porosity produced the highest error compared to other properties. This is very similar to the problem encountered and explained thoroughly in section 5.2.3.2. Despite this high deviation from the original fracture porosity values, the model indicates that it is relatively insensitive to the change in fracture porosity and thus would not considerably affect the production results. For instance, Figure 5-68 compares the difference in the generated production profiles using the Forward ANN tool between the actual fracture porosity and the one predicted by Inverse ANN-
2 model for Case-40. The difference between these two profiles is negligible despite the considerable difference between the two fracture porosities.

Figure 5-59: Mean error distribution per case for Inverse ANN-2 (polymer gel)
Figure 5-60: Mean error distribution per reservoir property (polymer gel)

Figure 5-61: Comparison of matrix porosity predicted by ANN and simulator (polymer gel)
Figure 5-62: Comparison of fracture porosity predicted by ANN and simulator (polymer gel)

Figure 5-63: Comparison of matrix permeability predicted by ANN and simulator (polymer gel)
Figure 5-64: Comparison of fracture permeability predicted by ANN and simulator (polymer gel)

Figure 5-65: Comparison of fracture spacing predicted by ANN and simulator (polymer gel)
Figure 5-66: Comparison of reservoir thickness predicted by ANN and simulator (polymer gel)

Figure 5-67: Comparison of water saturation predicted by ANN and simulator (polymer gel)
Figure 5-68: Effect of fracture porosity (pof) on production profiles (polymer gel)
Chapter 6
Development of Graphical User Interface (GUI)

It is important to present the developed proxy models in Chapter 5 in a user-friendly environment, which is readily accessible to end users, particularly reservoir engineers, who are not necessarily expert in neural networks but still can utilize these models to its fullest extent. For this purpose, GUIDE tool in MATLAB was used to build a Graphical User Interface (GUI) that encapsulates all the expert systems developed in this research. Consequently, the results and end products of this research become easily available in a user-friendly environment. The main objective of this chapter is to present the main components and features of this developed GUI.

The first two windows of the GUI are for navigation purposes. They allow the user to navigate through the six expert systems developed in this study. The first window asks the user to select between two cases: water flooding case and polymer gel flooding case, refer to Figure 6-1. Following the selection of either two cases, another window appears which asks the user to select between the three ANN models: Forward ANN model, for production prediction, Inverse ANN-1 model, for project design prediction and Inverse ANN-2, for history matching of reservoir properties. Figure 6-2 shows a snap shot of the second window accessed after selecting the polymer gel flooding case.

For Forward ANN models, there are two main panels to input data for reservoir properties and project design parameters within the specified ranges. The user can also use the “Example” pushbutton to fill the edit boxes with preliminary input data. After inputting the data, the user can select the “Plot Results” pushbutton to display three production profiles of oil rate, water cut and recovery factor. In addition, the results from the plots are automatically exported and saved into a spread sheet. Figure 6-4 and Figure 6-4 show examples of the Forward ANN’s GUI windows for water flooding case and polymer gel flooding case, respectively.
Figure 6-1: GUI’s first main window

Figure 6-2: GUI’s second main window (polymer gel flooding case)
Figure 6-4: GUI's window for Forward ANN model (water flooding)

Figure 6-4: GUI’s window for Forward ANN model (polymer gel)
For the inverse models, there are two main input panels: one for inputting production data and the other panel for inputting reservoir properties for Inverse ANN-1 and design parameters for Inverse ANN-2. For inputting production data, an abandonment rate of 10 STB/D can be used and thus filling the entire table is not necessary, refer to Figure 6-6 where the production table was filled up to an abandonment time of 1170 days where an abandonment rate of 9.48 STB/D was reached. Furthermore, the user also has the option to select the “Example” pushbutton to fill the GUI with preliminary input data, which can be then changed by the user.

After inputting the data, the user can select the “Estimate Design Parameters” pushbutton, for Inverse ANN-1 model or “Estimate Reservoir Properties” pushbutton, for Inverse ANN-2 model to generate the results for the given model. Figure 6-6 and Figure 6-6 display the GUIs developed for Inverse ANN-1, whereas Figure 6-8 and Figure 6-8 show the GUIs developed for Inverse ANN-2, for both water flooding and polymer gel flooding cases.
Figure 6-6: GUI's window for Inverse ANN-1 (water flooding)

Figure 6-6: GUI's window for Inverse ANN-2 (polymer gel)
Figure 6-8: GUI's window for Inverse ANN-2 (water flooding)

Figure 6-8: GUI's window for Inverse ANN-2 (polymer gel)
Chapter 7

Conclusion and Recommendations

Water flooding in naturally fractured reservoirs and dual permeability systems can become impractical and cause many production problems, due to the presence of highly conductive fractures that can cause premature water breakthrough and poor sweep efficiency of oil in the reservoir. The application of polymer gel solution to plug conduit fractures in such problematic reservoirs, is one of the common practical solution used in the industry to improve sweep and oil recovery from these naturally fractured reservoirs. The main objective of this research is to develop proxy ANN models for the implementation of water flooding and polymer gel flooding in naturally fractured systems that can be used to evaluate various production scenarios at a much efficient computational time compared to thermal reservoir simulators. A total of six proxy models were developed in this study. Three ANN models were designed for each scenario, water flooding and polymer gel flooding, as follows:

The first model, Forward ANN, is developed to generate production profiles for three main performance indicators: oil rate, water cut and recovery factor, at a given set of reservoir properties and design parameters within a pre-specified range. For water flooding scenario, the optimum ANN structure was designed with five hidden layers containing a total of 328 neurons. The production profiles were matched with an average error of 2.5%, 5.63% and 1.32% for recovery factor, oil rate and water cut, respectively. On the other hand, for polymer gel scenario, the optimum network’s topography contains six hidden layers with a total of 670 neurons. The results obtained from this structure have shown a mean error of 2.46%, 10.31% and 8.01% for recovery factor, oil rate and water cut, respectively.
The second proxy model, Inverse ANN-1, is developed to estimate project’s design parameters at a given production profile and combination of reservoir properties. The design parameters considered are: injection rate, producer flowing Bottom-Hole Pressure (BHP), drainage area, polymer and cross linker concentrations. The last two parameters are designed for the case of polymer gel flooding only. In both scenarios, water flooding and polymer gel flooding, the optimum neural network’s structure contains a single hidden layer with a total number of 7 and 9 neurons, for water flooding and polymer gel cases, respectively. The results from both structures indicated an average error of about 7% for all testing cases and an average error between 5% and 10% per design parameter.

The third expert system, Inverse ANN-2, is also another inverse-looking model to estimate various set of reservoir properties at a given production profile and design parameters. The reservoir properties considered in this model include: reservoir thickness, matrix and fracture porosity, matrix and fracture permeability, fracture spacing and initial water saturation. For both water flooding and polymer gel flooding scenarios, the optimum ANN structure contains six hidden layers with a total of 111 neurons, for the water flooding case, and 387 neurons for the polymer gel flooding case. The mean error for all testing cases was less than 20% for both models with an average error per reservoir property of 8 to 28%.

A few specific conclusions could be derived from this research as follows:

- Optimizing the number of data set and cases fed into the neural network to have a wide coverage of all possible scenarios and production trends is a very important factor in producing reasonable results from the network.
- Using scaled conjugate gradient backpropagation training algorithm (trainscg) and log-sigmoid (logsig) as a function in the hidden layers was found the most efficient combination to train the neural networks in this study.
- Selection of an optimum network’s structure and topography largely depends on the complexity of the ANN model and the type of problem to be solved for any given data set.

- In this study, it was realized that increasing the number of layers and number of neurons for Forward ANN and Inverse ANN-2 models considerably improve the results, especially to solve complex cases generated from the polymer gel flooding scenario. Five to six hidden layers were used to build the ANN structures for those models and almost double the total number of neurons were required for polymer gel flooding compared to water flooding.

- In this research, it was observed that Inverse ANN-1 model used to estimate project’s design parameters is the least complex model requiring only a single hidden layer to match the results from reservoir simulation.

- The application of various functional links and scaling of input and output data by taking the logarithm improves the network’s training efficiency and prediction capability.

- In this study, it was found that the injection rate is one of the most sensitive parameter affecting the production outcomes and thus was intensively used in many functional links’ operations to accelerate the network’s learning efficiency.

- It was realized that the network has some learning difficulties in predicting reservoir properties, in particular fracture porosity that have the least effect on production curves.

- The development of GUI provides an easy access to end users to test all proxy models built in this study in a user-friendly environment.

The following recommendations should be taken into consideration to further improve the results and outcomes from this research:
In this study, reservoir fluid’s composition and polymer gel specifications, such as molecular weight, density, viscosity and adsorption properties were kept constant. Further improvements to these proxy models could be achieved by testing various fluid’s compositions and properties.

Additionally, initial reservoir temperature and pressure were kept constant due to its high dependency on fluids’ compositions and specifications. Using various ranges of initial reservoir temperature and pressure should be considered to enhance the outcomes from this study.

Future studies should also test the model with different rock-fluid properties and relative permeability characteristics to widen the application of these proxy models.

Five-spot injection pattern was used to design the flooding projects in this study. Future work should consider utilizing more injection patterns found in the literature such as, 4-spot, 7-spot, 9-spot or line drive injection patterns.

Other project’s design parameters, such as injection rate, producer BHP and polymer gel concentration, were kept unchanged with production time for any given case. Future work should study the effect of changing these design parameters with production time, especially at the time of water breakthrough by reducing water injection rate and increasing gel concentration, for example.

Future studies should also consider utilizing horizontal wells in the model to maximize reservoir’s contact and minimize the effect of water conning caused by vertical wells.

Data set outside the specified range given in this study should be also tested to expand the applications of expert systems developed in this research.
References


Appendix A

Distribution of Input Parameters (polymer gel Case)
Appendix B

Example of Simulator Input File for Polymer Gel Flooding Case

INUNIT Field
WSRF WELL 1
WSRF GRID TIME
WSRF SECTOR TIME
OUTSRF GRID MASS ADSORP PPM ADSPCMP PRES RFW SO SW TEMP VISW
VISWCOM MOLFR VLKVCMP
OUTSRF WELL MASS COMPONENT ALL
OUTSRF SPECIAL MASSFRAC 'Inj' 'Water' WATER
    MOLEFRAC 'Inj' 'Water' WATER
    VOLFRAC 'Inj' 'XLinker' WATER
PARTCLSIZE 3.53147e-016   WPRN GRID 0
OUTPRN GRID MASS ADSORP PPM ADSPCMP PRES RFW SO SW TEMP VISW VISW
MASFR VLKVCMP W
OUTPRN RES NONE
**$ Distance units: ft
RESULTS XOFFSET       0.0000
RESULTS YOFFSET       0.0000
RESULTS ROTATION      0.0000 **$ (DEGREES)
RESULTS AXES-DIRECTIONS 1.0 -1.0 1.0

**$ Definition of fundamental cartesian grid
GRID VARI 25 25 3
KDIR DOWN
DI IVAR
25*2.035321e+01
DJ JVAR
25*2.035321e+01
DK ALL
1875*2.707163e+02
DTOP
625*5000

**$ Definition of fundamental cartesian grid

**$ DUALPERM

SHAPE GK

NULL MATRIX CON 1
NULL FRACTURE CON 1
DJFRAC CON 7.112095e+01
DIFRAC CON 7.112095e+01
DKFRAC CON 7.112095e+01
POR MATRIX CON 3.208224e-01
POR FRACTURE CON 4.327917e-03
PERMI MATRIX CON 1.967329e+02
PERMI FRACTURE CON 2.336656e+03
PERMJ MATRIX CON     1.967329e+02
PERMJ FRACTURE CON    2.336656e+03
PERMK MATRIX CON      1.967329e+01
PERMK FRACTURE CON    2.336656e+03
PINCHOUTARRAY CON     1

END-GRID

**$ Model and number of components

MODEL 5 5 5 4

COMPNAME  'Water' 'Polymer' 'XLinker' 'Gel' 'Oil'

CMM
18 10000 206 10206 100

IDEALGAS

TCRIT
647.4 0 0 0 0

PRSR 14.7

TEMR 120

PSURF 14.7

TSURF 58.14

MOLDEN
62.4 62.4 62.4 62.4 50

AVISC
0.5 0.5 4 0.5 1

VSMIXCOMP 'Polymer'

VSMIXENDP 0 1.8E-6

VSMIXFUNC 0 0.15 0.28 0.42 0.52 0.63 0.7 0.79 0.87 0.94 1
**$ Reaction specification

STOREAC

0 1 1 0 0

STOPROD

0 0 0 1 0

FREQFAC 3.23e+3

ROCKFLUID

RPT 1 WATWET

**$ Sw krw krow

SWT

0.25 0.0 0.9
0.5 0.1415 0.4245
0.78 0.3 0.0

**$ Sl krg krog

SLT

0.25 1.0 0.0
1.0 0.0 0.9

RPT 2 WATWET

**$ Sw krw krow

SWT

0.25 0. 0.9
0.3 0.002 0.69
0.4 0.03 0.33
0.5 0.06 0.13
0.6 0.14 0.04
0.7  0.2  0.005
0.78  0.3  0.
**$  Sl  krg  krog
SLT
0.25  1  0.
1.   0  0.9
ADSCOMP 'Gel' WATER
ADSLANG 15.3  0  5.55e6
ADSROCK 1
ADMAXT 0.0267e-4
ADRT 0.0267e-4
RRFT 40
ADSROCK 2
ADMAXT 0.0575e-4
ADRT 0.0575e-4
RRFT 80
ADSCOMP 'Polymer' WATER
ADSLANG 7.55e1  0  5.55e7
ADSROCK 1
ADMAXT 0.0136e-4
ADRT 0.0136e-4
RRFT 1.8
ADSROCK 2
ADMAXT 0.0572E-4
ADRT 0.0572E-4
RRFT 2.5

KRTYPE *MATRIX CON 2
KRTYPE *FRACTURE CON 2
ADSTYPE *MATRIX CON 1
ADSTYPE *FRACTURE CON 2

INITIAL

VERTICAL OFF

INITREGION 1

PRES *MATRIX CON 4000
PRES *FRACTURE CON 4000
TEMP *MATRIX CON 120
SW MATRIX CON 1.337760e-01

MFRAC_WAT 'Water'*FRACTURE CON 1
MFRAC_WAT 'Water' *MATRIX CON 1

NUMERICAL

TFORM ZT

ISOTHERMAL

RUN

DATE 2014 6 1

DTWELL 1e-007

**$

**$

WELL 'Inj'

INJECTOR UNWEIGHT 'Inj'

INCOMP WATER 9.999740e-01 2.907447e-06 2.313548e-05 0. 0.
TINJW 60.

OPERATE MAX STW 3876.732600 CONT

**$ rad geofac wfrac skin

GEOMETRY K 0.28 0.249 1. 0.

PERF GEOA 'Inj'

**$ UBA ff Status Connection

    1 1 3 1. OPEN FLOW-FROM 'SURFACE'

**$

**$

WELL 'Pro'

PRODUCER 'Pro'

OPERATE MIN BHP 3162.578300 CONT

**$ rad geofac wfrac skin

GEOMETRY K 0.28 0.249 1. 0.

PERF GEOA 'Pro'

**$ UBA ff Status Connection

    25 25 1 1. OPEN FLOW-TO 'SURFACE'

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DATE 2014 9 1.00000

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DATE 2014 11 1.00000

DATE 2014 12 1.00000

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