DEVELOPMENT OF ARTIFICIAL NEURAL NETWORKS
APPLICABLE TO SINGLE PHASE UNCONVENTIONAL GAS
RESERVOIRS WITH SLANTED WELLS

A Thesis in
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by
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ABSTRACT

The increasing demand in energy has strengthen the dependence on fossil fuels. On the other hand, the conventional hydrocarbon reservoirs are depleting rather quickly which prompted an important study of the hydrocarbon reservoirs from unconventional reservoirs. Over the last two decades, the improvement in technology and recovery methods has allowed the industry to extract hydrocarbon from unconventional reservoirs. There are been important advancements in drilling and reservoir engineering technologies.

In order to overcome some of the costs associated with the exploitation of those reservoirs, an extensive use of techniques such as directional drilling to has been largely recommended and has proven to be more efficient. Directional drilling allows to control the direction of the wellbore to increase the contact with the target or pay zone location among other significant benefits.

Reservoir simulation refers to constructing computer models to gain a better understanding of reservoirs. It is mostly used to predict the flow of fluids or to match the properties of the reservoir. However, it has shown to have be limited when not enough information about the reservoir is available.

Artificial neural network (ANN) is a technique used in many fields that has been able to compensate for some of the limitations associated with other approaches such as reservoir simulation. It relies on observed data to build highly non-linear and strong links among them that make it possible to obtain a more accurate prediction of the missing information.
The main goal of this study is to develop an ANN tool for a single phase unconventional gas reservoir that can predict reservoir properties such as porosity, permeability and compressibility. The tool applicability has been extended for a large range of data. It provides predictions from two network structures, cascade forward backpropagation and radial basis function with an option to compare them. Each of the ANN model, therefore, differs by the type of networks used, the porosity system (single or dual), the well inclination (0 to 90°), and the transient data available (pressure or production rate). The performance of each network was evaluated using the average percent error, the mean bias error (MBE), and the root mean square error (RMSE).
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Chapter 1 INTRODUCTION

The demand for energy keeps reaching higher level along with the world population and therefore, the number of households. Electricity, heat and transportation are sectors that are greatly dependent on reliable energy sources. Among them, fossil fuels, including petroleum, coal and natural gas, are the most important followed by renewable energy and nuclear fuels. Although fossil fuels have some negative effects such as carbon dioxide emission, associated with global warming and climate change, their use is increasing at an important rate. Also, the petroleum has been decreasing at a very high rate which led to an expansion in technique for hydrocarbon from unconventional reservoirs to match the demand. In the last two decades, natural gas recovery has exponentially increased to fill this gap.

Natural gas has become one of the most important source of energy due to the advancement in technology and recovery techniques. Conventional reservoirs did not require so many tools and skills which is one of the reasons they are depleting so quickly over time. Also in recent decades, new techniques such as hydraulic fracturing allowed the production from low permeability shale rock which made the United States the first Natural gas producer. Hydraulic fracturing is being used in more countries worldwide following its success in North America. Along with hydraulic fracturing, directional and horizontal drilling are often associated with hydrocarbon extraction from unconventional gas reservoirs.

Directional and horizontal drilling which mostly consists of drilling non-vertical wells has become really attractive over time. Although those wells still have a
vertical section mostly before reaching their targets, the slanted section allows to increase pay zone length. In other words, a single non-vertical well is capable to follow reservoir trajectory which would have required multiple vertical wells. There are lot of other benefits associated with using non-vertical wells such as the fact that they can all be drilled from the same location and access reservoir that are located anywhere, even under a town. Also, they can go in the direction of the maximum fractures in a fractured reservoir to increase productivity. There have been a lot of improvement in reservoir engineering techniques to predict reservoir properties as well.

One of the most common approach used to predict reservoir properties is reservoir simulation which carries a certain range of uncertainties due to the numerous assumptions that have to be made to create a model. Reservoir simulation are constantly updated with the availability of more data which is a tedious and time-consuming process. Artificial neural network used in different field is more attractive and has proved to provide accurate results in petroleum engineering. It is able to decrease the range of uncertainties substantially by first learning from experience rather than from several assumptions and being able to instantaneously provide predictions. Artificial neural network allows to create machines that have an understanding for a wide variety of reservoir models and are capable to provide the missing pieces of information in a timely manner.

The present study focuses on developing an artificial neural network tool for a single gas phase reservoir with a slanted well. The tool accounts for a single or double porosity medium as well as pressure or rate transient data. A computer programming software, Matrix Laboratory (MATLAB), is used to generate
reservoir and well variables within a specified range. Then a reservoir simulator, Computer Modeling Group (CMG), uses those variables to predict production or pressure data versus time for a period of 40 years. Then MATLAB is used to compiled the data and reorganize it for its built-in artificial neural network training tool. The trained networks are combined in a user friendly graphical user interface, GUI. Thus, the user will have to provide the type of porosity, the angle inclination and the data available to be directed toward the appropriate network.

This study is summarized in sections with a literature review in Chapter 2 that provides information about unconventional gas reservoirs, non-vertical wells, the reservoir porosity models, the transient data and a brief overview of the artificial neural network history, then a problem statement in Chapter 3. Chapter 4 is a more detailed summary of the ANN used in this study and Chapter 5 provides a step by step development of the networks from the variables generation to the graphical user interface. Chapter 6 presents the results obtained followed by a throughout discussion about their implication. Chapter 7 is a summary and a conclusion of the entire work.
Chapter 2 LITERATURE REVIEW

This chapter provides a brief description of unconventional gas reservoirs, reservoir data analysis, porosity models and artificial neural network.

2.1. UNCONVENTIONAL GAS RESERVOIRS

The natural gas industry has come a long way since the reporting of natural gas sweeps in Ontario County, New York in 1669 by the French explorer, M. de La Salle and French missionary M. de Galinee. Due to the lack of pipeline network, the gas was mostly used to light streets at night before the advancement of electric lamps in the late 1800s. In fact, with the electric lamps, it is the research for alternate market that contributed to the piping of gas to other towns to for lighting, heat and supply energy for the drilling of oil wells by the 1880s. By the end of the nineteen century, gas companies were developing longer intrastate pipelines and municipal natural gas distribution systems and the first gas storage facility in the United States was developed in 1916 (Islam, 2014).

Another important advancement in the natural gas industry is hydraulic fracturing. Hydraulic fracturing has been around since the 1860s, however, it only consisted in exploding torpedoes in wells. It was not before the 1940s that companies put more effort into finding ways to keep the wells open. In the 1970s, hydraulic fracturing became popular and help increase production for long periods while depleting some of the fields. Most of those fields were converted to gas storage fields. In the late 1990s and early 2000s, hydraulic fracturing has become more important with technological advances in three-dimensional seismic imaging, directional drilling, and well completion when companies starting expanding explorations in shale formations (Islam, 2014).
With all those advancements in technology, unconventional gas reservoirs have known an impressive production and like shown in Figure 2-1, natural gas is expected to show the highest growth in the 30-year projection (EIA, 2016).

![Figure 2-1 Energy production history and projections (EIA)](image)

Figure 2-2 provides more information concerning the largest contributors to natural gas growth. Shales gas, tight oil and tight gas plays are the main contributors and are expected to account nearly more than two thirds of total U.S. production by 2040 (EIA, 2016).

![Figure 2-2 Dry Natural Gas production by type history and projections (EIA)](image)
2.2 DIRECTIONAL DRILLING

In the 1920s, the industry became aware that wellbore supposedly vertical maybe subject to deviation caused by faults, bedding planes, and formation dips. It was the beginning of decades long of research for methods to control the wellbore direction as summarized in Figure 2-3.

![Figure 2-3 Evolution of Directional Drilling (IADC, 2012)](image)

Figure 2-4 presents a vertical (cross section) and horizontal view (top) of a directional well. As shown in this figure, directional drilling is interesting because it allows to reach a target from a remote location. Directional drilling can be applied for sidetracking (deviate from the existing well), to avoid geological problems (such as salt domes), to control vertical holes, to drill beneath inaccessible locations, for offshore development, and even non-petroleum uses (Inglis, 2005).
However, there are a lot of considerations that should be taken when studying horizontal or inclined wells. In the case of horizontal wells, it is important to consider the frictional losses, the pressure drops they create and the effect on the drawdown and consequently the production. It has been determined that there exists an optimum well length beyond which the frictional losses cannot be neglected. In this range, the productivity is reduced significantly. Therefore, one should be cautious when dealing with horizontal wells (Novy, 1995).

Furthermore, it has been shown that besides pressure drop due to friction, acceleration and gravity, a pressure drop due to inflow should be considered. It has been shown that inflow as well as outflow affect wall friction shear. Inflow from productions wells increases wall friction for laminar flow and decreases for turbulent flow (Ouyang, Arbabi, and Aziz, 1998)
2.3. RESERVOIR TRANSIENT DATA

Pressure transient analysis and rate transient analysis consisted of studying the data obtained from production to obtain more information about the reservoir. Pressure transient analysis consists of producing at a constant flow rate and keep track of the change in pressure with time while rate transient analysis consists of producing at constant bottom-hole pressure and track the change in flow rate with time. There are a lot of transient tests being performed on a field at different stage of a field project such as drillstem test, buildup test, or falloff test. The objective is to obtain reservoir properties such as permeability, fracture length, reservoir pressure, or porosity (Kamal, Freyder, and Murray, 1995).

2.4. DUAL-POROSITY MODEL

The dual porosity model is one of the most flow model used for the simulation of fractured reservoirs. The approach is based on the fact that two types of medium are presented in a fractured reservoir, the matrix and the fracture. The matrix has the higher porosity but a low permeability while the fracture has a high permeability but a low porosity. Besides, the exchange of fluid between both media is proportional to their pressures. Barenblatt, and Zheltov introduced the first model in 1960. Their model consists of equations for the fracture, the matrix, and the transfer between them with the assumption that the flow occurred at pseudo-steady state (Barenblatt, Zheltov, and Kochina, 1960).

In 1963, Warren and Root come up with their model presented in Figure 2-5.
In this model, the matrix is represented by blocks and the fracture represent the space between the blocks. This model uses a shape-factor to describe the flow from the matrix to the fracture (Warren and Root, 1963).

**Figure 2-5** Warren and Root Dual Porosity Model
2.5. Definition and History of the Artificial Neural Network

A neural network is a massively parallel distributed processor made up of simple processing units that have a natural tendency of storing experiential knowledge from its environment through a learning process using interneuron connection strengths known as synaptic weights. In other words, a neural network which is inspired from the biological brain has the capability to organize its neurons to perform computations many times faster than the fastest digital computer in existence today. Figure 2-6 *The pyramidal cell* shows a type of cortical neural known as the pyramidal cell. It receives most of its inputs through dendritic spines then send signals along the axon to other neurons (Haykin, 2009).

*Figure 2-6* The pyramidal cell (Haykin)
In 1958, Frank Rosenblatt came up with the idea of the perceptron. A mathematical model that represents the human brain by taking inputs, neurons, and multiplying each by a weight, synapse strength to each nearby neuron. Then all the weighted inputs are added together and if the sum is big enough the output is a 1 otherwise the output is a 0 (Rosenblatt, 1958).

The first computational model for neural networks was created in 1943 by Warren McCulloch and Water Pitts. They wrote a paper on how neurons might work while performing some logical reasoning (McCulloch and Pitts, 1943).

In 1949, Donald Hebb presented a work that showed that neural pathways become stronger each time they are used. It is well known for the Hedd’s law that stated that “Neurons that fire together wire together”. In order words, learning and knowledge are due to the connection of synapses between neurons (Hebb, 1949).

The only way for a neural network to learn was to be trained. A training sets with inputs and targets could then be used to teach the network. By starting with some random weights, an output can be computed then compared with the target. If they do not match the output the weights are adjusted and the process repeated. The action of assigning a weight to each input is known as an epoch and is used in the training process to determine how many times the operation is executed. Figure 2-7 Perceptron Diagram provides a preview of a perceptron. $x_i$ represents the input, while $w_i$ represent the weight. b is the bias input that has a value of 1 and is used to add some flexibility to the activation function and improve the data prediction. Once the output is computed the network retains the connection between the input-output known as the activation function. The training stops once the error between output and target reaches a certain goal. Once a neural network is trained can be evaluated by using a different set of inputs, testing set.
In 1959, Bernard Widrow and Marcian Hoff developed “ADALINE” and “MADALINE”. ADALINE, adaptive linear elements, was a binary pattern recognizer while MADALINE was the first neural network applied to real life problem. In 1962, they developed a learning procedure to minimize error over all training patterns known as the delta rule. It consisted in distributing a perceptron error across the network by adjusting the weight values without using an activation function (Widrow and Hoff, 1960).

However, the main purpose of an artificial network was to be able to perform task as the human brain and solve difficult problems that are non-linear. Therefore, there was a need to use non-linear activation function and to build networks that can provide more than one output for more realistic and complex problems. To massage the complexity of those problems an intermediate layer, hidden layer, can be used to perform some computation between the input layer and output layer. The first multilayered network was developed in 1975. The issue became in the adjustment of weights among layers.

In 1986, the Widrow-Hoff rule was extended to multilayers by David Rumelhart, Geoffrey Hinton, and Ronald Williams in what is known as backpropagation. Although they did not come up with the idea, they were able to present in a way

**Figure 2-7 Perceptron Diagram**

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In 1986, the Widrow-Hoff rule was extended to multilayers by David Rumelhart, Geoffrey Hinton, and Ronald Williams in what is known as backpropagation. Although they did not come up with the idea, they were able to present in a way
that could be understood by many and solve most of the problems encountered with neural networks at the time. In a few words, backpropagation mostly consists of first going forward, by evaluating the outputs from a set of inputs, compare it with the target using a loss function, then use the error to compute the gradient of the loss function then go backward and adjust the weight from the neurons in the previous layers (Rumelhart, Hinton, and Williams, 1986).

Their formulation was able to bring the artificial neural networks curiosity back. They are since being a lot of involvement and improvement and artificial neural networks is used to solve problems in many fields such as petroleum engineering.
Chapter 3 PROBLEM STATEMENT

In the petroleum industry, the key to success is sometimes determined by how accurate the information about the reservoir is. If it was possible to determine ahead of time before investing anything into it what properties such as porosity and permeability are, the best strategies available would be deployed to maximize the hydrocarbon recovery. However, from discovery to abandonment the main achievement concerning those properties goes toward decreasing the range of uncertainty they carry. Among many tools available, reservoir simulation has been able to predict the viability of a field using those ranges and many assumptions for the missing data. A most recent technology, artificial neural network, has been able to deal with greater care with those uncertainties and provides an average value for the missing data.

Artificial neural network is able to provide a more insightful meaning about reservoir data via the strong connection between well and reservoir data. It is basically a brain that just needs to learn from the provided input and output data to create links among them. A trained network can be used for fields with a lot of similarities as long as all the inputs required are provided and give results that have been proven to be close enough to the actual outputs. In doing so, it is taking care of many uncertainties and timing associated with many other tools. With such a tool in hand, it is possible to determine how to move forward with the development plan of a field more efficiently.

This study focused on the development of neural networks for a single gas phase reservoir with a well at different inclination. Each of these networks will require
inputs such as the gas specific gravity $S_g$, reservoir area $A$, thickness $h$, initial pressure $P_i$ and temperature $T_i$, as well as the well daily production data ($q_g$ or $P_{wf}$) vs time and specification ($q_{sp}$ or $P_{sp}$) in order to provide reservoir information such as the porosity ($\phi$ and $\phi_f$), permeability ($k$ and $k_f$) and compressibility ($C_m$ and $C_f$). The outcome of the study is therefore to provide the user with a machine that can provide those reservoir properties in a matter of seconds. Figure 1 provides a simplified version of how this machine is made.

Figure 3-1 Flow chart of a neural network development
Chapter 4 ARTIFICIAL NEURAL NETWORK

This chapter provides a description of the types of ANN used in this study, their differences and the steps taken during the training.

4.1 TYPES OF ANN

There are a lot of artificial neural networks types today. The most common are multi-layer perceptron (MLP), radial basis function (RBF), perceptron network, and Kohonen network. For this study, two types of networks were considered. One is a cascade forward backpropagation network, and the radial basis function network. To create a cascade-forward backpropagation network, newcf is used in MATLAB. The following information is needed:

- Normalized Input
- Normalized Target
- Number of layers and neurons in each layer
- Transfer Function for each layer
- Training function
- Learning Algorithm

To create a radial basis function, newrb is used in MATLAB, the following information is needed:

- Normalized Input
- Normalized Target
- The mean square error goal
- Spread
- Maximum number of neurons
- The number of neurons to be added between each epoch
In order to create an artificial neural network, a data set is required. It is then divided into three subsets, training, validation, and testing sets. During the training, the network uses the training sets to adjust the weights, then the validation sets to minimize overfitting. The validation set is used to track the network response to a different set and to avoid overfitting. Accuracy is expected to increase as the training process is ongoing but sometimes the validation’s accuracy does not follow the same trend as the training accuracy and it is a sign that the training should be stopped. Once the network is trained the testing sets is used to confirm its performance and provide the strength of the network (Haykin, 2009).

There are a lot of steps that can be taken to improve the network depending on the type of network such as changing the number of hidden layers, the functional links, the activation function, the learning algorithm or ultimately the type of network.

### 4.2 Cascade Forward Back Propagation ANN

#### 4.2.1 Description

The cascade forward back propagation network differs from other feed forward back propagation network because it allows a connection between a layer to all the following layers as presented in Figure 4-1.

![Figure 4-1](image.jpg)  
**Figure 4-1** Example of Cascade Forward Back Propagation Network Structure
4.2.2 TRANSFER FUNCTION

The activation function or transfer function is used in a neuron to limit the permissible amplitude range of the output signal to some finite value. In other words, it takes the sum of the weighted inputs and the bias and depending on the magnitude of this sum, it return a value in the range \([0,1]\) or \([-1,1]\) (Haykin, 2009).

Table 4-1 Common Transfer Functions

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Function Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tanh sigmoid</td>
<td>( f(x) = \frac{2}{1 + e^{-2x}} - 1 )</td>
</tr>
<tr>
<td>Log Sigmoid</td>
<td>( f(x) = \frac{1}{1 + e^{-x}} )</td>
</tr>
<tr>
<td>Linear</td>
<td>( f(x) = x )</td>
</tr>
</tbody>
</table>

The activation function allows the learned function during the training to be non-linear which would not solve some of the most realistic problems. The transfer function used in this study are presented in Table 4-1.
The gaussian transfer function, radbas, is used in radial basis networks while the
tanh-sigmoid and log-sigmoid functions, tansig and logsig respectively are used in
multilayer neural network such as cascade forward backpropagation network.

4.2.3 TRAINING ALGORITHM AND FUNCTIONS

The main goal of a training algorithm is to decrease the total error function and by
finding the most appropriate value of the weights and biases. If the weights are
given by $w_k$ at each iteration $k$ and the total error function by $E$, the update rule is
given by

$$w_{k+1} = w_k - \alpha_k \frac{\partial E}{\partial w} \quad (4.1)$$

The different algorithms differ in how they define the learning rate, $\alpha_k$, which
represents the step size and the gradient $\frac{\partial E}{\partial w}$ which represents the search direction.

In other words, during training the weights have to be updated to minimize the
differences among the targets and outputs and there are two uncertainties, one in
the direction to take and the other in how far to go.

Table 4-2 Type of Training Algorithms and Functions

<table>
<thead>
<tr>
<th>Algorithm Name</th>
<th>Function Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gradient descent backpropagation</td>
<td>traingd</td>
</tr>
<tr>
<td>Gradient descent with momentum backpropagation</td>
<td>traindgm</td>
</tr>
<tr>
<td>Gradient descent with adaptive lr backpropagation</td>
<td>trainlda</td>
</tr>
<tr>
<td>Levenberg-Marquardt backpropagation</td>
<td>trainlm</td>
</tr>
<tr>
<td>BFGS quasi-Newton backpropagation</td>
<td>trainbfg</td>
</tr>
<tr>
<td>One step secant backpropagation</td>
<td>trainoss</td>
</tr>
<tr>
<td>Scaled conjugate gradient backpropagation</td>
<td>trainscg</td>
</tr>
<tr>
<td>Bayesian regularization</td>
<td>trainbr</td>
</tr>
<tr>
<td>Powell -Beale conjugate gradient backpropagation</td>
<td>traincgb</td>
</tr>
</tbody>
</table>
The training algorithms and functions presented in Table 4-2 can be divided into three main groups, gradient descent, conjugate gradient, and quasi newton algorithms. Each of them differ in the type of problems, the speed and the memory required. Only two of those functions were used in this study, trainlm and trainscg.

Levenberg-Marquardt Algorithm

The Levenberg-Marquardt Algorithm is well-known for its fast and stable convergence. It is more suitable for training small and medium-sized problems (Yu and Wilamowski, 2011). The update rule is given by

\[ w_{k+1} = w_k - (J_k^T J_k + \mu I)^{-1} J_k e_k \]  \hspace{1cm} (4.2)

k is the index of iteration.

Before defining the other terms, it is important to understand what happens during the training process and how the Levenberg-Marquardt algorithm is built upon other algorithms.

Given the inputs and targets, an initial set of weights is selected and the error computed by

\[ E(x, w) = \frac{1}{2} \sum_{p=1}^{P} \sum_{m=1}^{M} e_{p,m}^2 \]  \hspace{1cm} (4.3)

x is the input vector, w is the weight vector, p and m the input and output indexes respectively. P and M are the number of input and output respectively. \( e_{p,m} \) is the training error, target-output.
The steepest descent algorithm uses the gradient \( g \), the first order derivative of the total error function

\[
g = \frac{\partial E(x,w)}{\partial w} = \left[ \frac{\partial E}{\partial w_1} \frac{\partial E}{\partial w_2} \cdots \frac{\partial E}{\partial w_N} \right] \tag{4.4}
\]

\( N \) the total number of weights

Which when combined with equation (4.1) gives

\[
w_{k+1} = w_k - \alpha_k g_k \tag{4.5}
\]

The Newton’s Method goes one step further by considering the fact all weights are linearly independent and therefore they can be represented with a nonlinear function with the related gradients exponents.

\[
g_i = F_i(w_1, w_2 \ldots w_N)
\]

A Taylor series expansion with first order approximation will give

\[
g_i = g_{i,0} + \frac{\partial g_i}{\partial w_1} \Delta w_1 + \cdots + \frac{\partial g_i}{\partial w_N} \Delta w_N \tag{4.6}
\]

Which is equivalent to

\[
g_i = g_{i,0} + \frac{\partial}{\partial w_2} \frac{\partial E}{\partial w_i} \Delta w_1 + \cdots + \frac{\partial}{\partial w_N} \frac{\partial E}{\partial w_i} \Delta w_N = g_{i,0} + \frac{\partial E}{\partial w_i \partial w_2} \Delta w_1 + \cdots + \frac{\partial E}{\partial w_i \partial w_N} \Delta w_N
\]

With the goal of the training to have zero error at the end, it is possible to write

\[
g_{i,0} + \frac{\partial E}{\partial w_i \partial w_1} \Delta w_1 + \cdots + \frac{\partial E}{\partial w_i \partial w_N} \Delta w_N = 0
\]

Which can be rearranged as

\[
-g_{i,0} = \frac{\partial E}{\partial w_i \partial w_1} \Delta w_1 + \cdots + \frac{\partial E}{\partial w_i \partial w_N} \Delta w_N = -\frac{\partial E}{\partial w_i}
\]
Or in a matrix form as

\[
\begin{bmatrix}
-g_1 \\
\vdots \\
-g_N
\end{bmatrix}
= 
\begin{bmatrix}
\frac{\partial E}{\partial w_1} & \cdots & \frac{\partial^2 E}{\partial w_1 \partial w_N} \\
\vdots & \ddots & \vdots \\
\frac{\partial E}{\partial w_N} & \cdots & \frac{\partial^2 E}{\partial w_N \partial w_1}
\end{bmatrix}
\begin{bmatrix}
\Delta w_1 \\
\vdots \\
\Delta w_N
\end{bmatrix}
\]

The Hessian Matrix, H, is then defined as

\[
H = 
\begin{bmatrix}
\frac{\partial^2 E}{\partial w_1^2} & \cdots & \frac{\partial^2 E}{\partial w_1 \partial w_N} \\
\vdots & \ddots & \vdots \\
\frac{\partial^2 E}{\partial w_N \partial w_1} & \cdots & \frac{\partial^2 E}{\partial w_N^2}
\end{bmatrix}
\]

The entire equation can be re-written as

\[-g = H \Delta w \rightarrow \Delta w = w_{k+1} - w_k = -H_k^{-1} g_k\]

The update rule for Newton’s method

The Gauss-Newton Algorithm simplified the difficulty that might arise from trying to compute the second-order derivative of the total error function. As defined earlier,

\[g_i = \frac{\partial E}{\partial w_i} = \frac{1}{2} \frac{\sum_{p=1}^{P} \sum_{m=1}^{M} e_{p,m}^2}{\partial w_i} = \sum_{p=1}^{P} \sum_{m=1}^{M} \left( \frac{\partial e_{p,m}}{\partial w_i} \right) e_{p,m} \text{ after differentiation}\]

The Jacobian matrix, J, was then introduction as

\[
J = 
\begin{bmatrix}
\frac{\partial e_{1,1}}{\partial w_1} & \cdots & \frac{\partial e_{1,1}}{\partial w_N} \\
\vdots & \ddots & \vdots \\
\frac{\partial e_{p,m}}{\partial w_1} & \cdots & \frac{\partial e_{p,m}}{\partial w_N}
\end{bmatrix}
\]
Therefore,

\[ g = Je \]

With \( e \) the error vector given by

\[
e = \begin{bmatrix} e_{1,1} \\ \vdots \\ e_{1,M} \\ \vdots \\ e_{P,1} \\ \vdots \\ e_{P,M} \end{bmatrix}
\]

The element of the Hessian Matrix can be represented as

\[
h_{i,j} = \frac{\partial^2 E}{\partial w_i \partial w_j} = \frac{\partial^2}{\partial w_i \partial w_j} \left( \frac{1}{2} \sum_{p=1}^{P} \sum_{m=1}^{M} e_{p,m}^2 \right) = \sum_{p=1}^{P} \sum_{m=1}^{M} \left( \frac{\partial e_{p,m}}{\partial w_i} \frac{\partial e_{p,m}}{\partial w_j} + \frac{\partial^2 e_{p,m}}{\partial w_i \partial w_j} e_{p,m} \right)
\]

By assuming that \( \frac{\partial^2 e_{p,m}}{\partial w_i \partial w_j} e_{p,m} = 0 \),

\[
h_{i,j} = \sum_{p=1}^{P} \sum_{m=1}^{M} \left( \frac{\partial e_{p,m}}{\partial w_i} \frac{\partial e_{p,m}}{\partial w_j} \right) \rightarrow H = J^T J
\]

Therefore, the updating rule for the Gauss-Newton algorithm is

\[
w_{k+1} = w_k - H_k^{-1} g_k = w_k - (J^T J)_k^{-1} J_k e_k
\]

The issue with this algorithm is the possibility for \( J^T J \) to be non-invertible.

The Levenberg-Marquardt algorithm fixed that issue by adding the combination coefficient \( \mu \) that is always positive such that

\[
H = J^T J + \mu I
\]

I is the identity matrix.
Scaled conjugate gradient algorithm

The scale conjugate gradient backpropagation was introduced in 1990 by Martin F. Moller to overcome the limitations of the other conjugate gradient algorithms that require a line search to determine the step size in each iteration. This algorithm uses a Levenberg-Marquardt approach to scale the step size (Møller, 1993).

The conjugate gradient algorithms are based on the conjugate gradient method. Instead of changing direction along the steepest gradient, the conjugate direction is used. It should be recalled that a set of vectors \( \{p_k\} \) is mutually conjugate with respect to a positive definite Hessian matrix \( H \) if and only if

\[
p_k^T H p_j = 0 \quad k \neq j \quad \text{(Hagan, Demuth, and Beale)}
\]

In order to avoid the computation of the Hessian matrix, some previously defined relationships can be used. From the Newton’s method,

\[
H_k \Delta w = -\Delta g_k
\]

Knowing that

\[
\Delta w_k = -\alpha_k g_k \quad \text{and} \quad p_k = -g_k \rightarrow \Delta w_k = \alpha_k p_k
\]

The following relationship is derived

\[
\alpha_k p_k^T H p_j = \Delta w_k^T H p_j = \Delta g_k^T p_j \quad k \neq j
\]

Therefore, it becomes possible to find a search direction by beginning the search with the steepest gradient direction, \( p_0 \), such that

\[
p_0 = -g_0 = -\frac{\partial E}{\partial w}
\]
Then a learning rate, $\alpha_k$, is selected to minimize the function along the search direction.

Then a vector $p_k$, orthogonal to the gradient vector is computed at each iteration

$$p_{k+1} = -g_k + \beta_k p_k$$

If there is no convergence, the learning rate is recalculated and the steps repeated.

The conjugate gradient algorithms differ in the definition of the scalars $\beta_k$.

The scaled conjugate gradient algorithm is following the same logic as the others conjugate gradients methods by avoiding the difficulty of directly determining a Hessian matrix but goes a step further by avoiding the calculation complexity per iteration associated with the line search. A scalar $\lambda_k$, inspired from the Levenberg-Marquardt approach, was introduced to control the indefiniteness of the second order derivative of the total error function. The scaled gradient algorithm is therefore defined as follow (Møller, 1993):

1. Choose the weight vector $w_1$ and scalars $\sigma > 0, \lambda_1 > 0, \text{and } \bar{\lambda}_1 = 0$

Set $p_1 = r_1 = -E'(w_1)$, $k=1$ and success=true

2. If success=true then calculate second order information

$$\sigma_k = \frac{\sigma}{|p_k|}, \quad s_k = \frac{E'(w_k + \sigma_k p_k) - E'(w_k)}{\sigma_k}, \text{and } \delta_k = p_k^T s_k$$

3. Scale $s_k$:

$$s_k = s_k + (\lambda_k - \bar{\lambda}_k)p_k$$

$$\delta_k = \delta_k + (\lambda_k - \bar{\lambda}_k)|p_k|^2$$

4. If $\delta_k \leq 0$ then make the Hessian matrix positive definite
\[ s_k = s_k + \left( \lambda_k - 2 \frac{\delta_k}{|p_k|^2} \right) p_k \]

\[ \bar{\lambda}_k = 2 \left( \lambda_k - \frac{\delta_k}{|p_k|^2} \right) \]

\[ \delta_k = -\delta_k + \lambda_k |p_k|^2, \lambda_k = \bar{\lambda}_k \]

5. Calculate step size:

\[ \mu_k = p_k^T r_k, \quad \alpha_k = \frac{\mu_k}{\delta_k} \]

6. Calculate the comparison parameter:

\[ \Delta_k = \frac{2\delta_k [E(w_k) - E(w_k + \alpha_k p_k)]}{\mu_k^2} \]

7. If \( \Delta_k \geq 0 \) then a successful reduction in error can be made

\[ w_{k+1} = w_k + \alpha_k p_k, \]

\[ r_{k+1} = -E'(w_{k+1}) \]

\[ \bar{\lambda}_k = 0, success = true \]

if \( k \) mod \( N \) = 0 then restart the algorithm: \( p_{k+1} = r_{k+1} \)

else create new conjugate direction:

\[ \beta_k = \frac{|r_{k+1}|^2 - r_{k+1} r_k}{\mu_k}, p_{k+1} = r_{k+1} + \beta_k p_k \]

If \( \Delta_k \geq 0.75 \) then reduce the scale parameter: \( \lambda_k = \frac{1}{2} \bar{\lambda}_k \)

Else a reduction in error is not possible: \( \bar{\lambda}_k = \lambda_k, success = false \)

8. If \( \Delta_k < 0.25 \) then increase the scale parameter: \( \lambda_k = 4 \lambda_k \)
9. If the steepest descent direction $r_k \neq 0$ then set $k=k+1$ and go to 2 else terminate and return $w_{k+1}$ as the desired minimum.

4.2.4 Training Steps in MATLAB

The first step consists in importing the input and target data, then normalize them using mapminmax. Mapminmax maps the minimum and maximum to values between -1 and 1. The dataset (500) is then randomly divided into training (400), validation (50), and testing (50) sets.

MATLAB has a build-in function newcf which creates a cascade-forward backpropagation network. To create a network, net, the following command is used.

```matlab
net = newcf(Pn. Tn, [n1, n2, ...], [tf1, tf2, ...], TF, LF, PF)
```

where, Pn (normalized input), Tn (normalized target), ni(number of neurons in layer i), tfi(transfer function of layer i), BTF, (training function), LF(weight/bias learning function), and PF(performance function).

The network is then configured for training by providing parameters such as the maximum number of epochs to train (net.trainParam.epochs), the performance goal (net.trainParam.goal), and the maximum validation failure (Param.max_fail). There are more training parameters that can be added to train the network.

The final step is to train and validate the network. For this part, the following command is used.

```matlab
[net, tr] = train(net, training_input, training_output, [], [], validation_input, validation_output)
```

Once the training is done, the trained network is simulated using the training dataset and the test sets. Then the results are mapped back to exact values and compared to
determine the network efficiency. If the network ends up having a poor performance they are some steps that can be taken such as changing the number of layers and neurons.

4.3 RADIAL BASIS FUNCTION ANN

4.3.1 DESCRIPTION

The radial basis function network is a two-layer network differ from the cascade forward backpropagation and other feedforward networks in many ways. First, the network does not perform an inner product between the weights and the input vectors. Instead, the distance between the input vector and the rows of the weight matrix is computed then multiplied by the bias. The bias is actually a required parameter for the training known as the spread. Second, the network contains one hidden layer and the number cannot be determined in advance. Depending on the definition of the problem, input and output, and the training parameters selected, the network will add one neuron at the time until the accuracy reaches a specific value. There are a lot of transfer functions that can be used in a RBF network. For this study, the gaussian function presented in Table 4-3 Transfer function for RBF Network was used.

Table 4-3 Transfer function for RBF Network

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Gaussian Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>$f(x) = e^{-x^2}$</td>
<td>radbas</td>
</tr>
</tbody>
</table>

![Graph of Gaussian Function]
Figure 4-2 shows an overview of the complete RBF network.

There are several training algorithms that can be used by RBF network but the most commonly used have two stages (Hagan, Demuth, and Beale). For the purpose of this study the Levenberg-Marquardt and the scaled conjugate gradient algorithms are used.

4.3.2 TRAINING STEPS IN MATLAB

The MATLAB function newrb is used to create a radial basis function network. This network has three layers, input layer, hidden layer, and output layer. The data is normalized using the function mapstd, then randomly divided into training, validation, and testing sets. The network, net, is created using the following command:

```matlab
net = newrb(Pn, Tn, goal, spread, maximum_neurons, neuron_to_be_added)
```
where, Pn (normalized input), Tn (normalized target), goal (the mean square error goal), and the spread (a number between 1 and 60)

The radial basis function network starts with one neuron, check if the goal is reached, if not one neuron is added. This process is repeated until either the goal. The maximum number of neurons attained

The network is then configured for training by providing parameters such as the maximum number of epochs to train (net.trainParam.epochs), the performance goal (net.trainParam.goal), and the maximum validation failure (Param.max_fail). There are more training parameters that can be added to train the network. Then it is trained using the following command

\[ [\text{net}, \text{tr}] = \text{train(} \text{net, training_input, training_output}) \]

The network is then simulated and the performance examined. Again, there are some steps that can be taken to improve performance. However, due to the relatively fast training speed, the radial basis network was pretty helpful in providing information about the most appropriate functional links.

4.4 Training Performance Evaluation

For this study, the approach was mostly making sure that there was no overfitting, then check the sensibility of the network for each input to determine the structure that would be advantageous for all the inputs combined. Some inputs have a stronger effect on the performance compared to others. The performance of each network is evaluated using the statistical analysis involving the mean bias error (MBE), the root means square error (RMSE), and the average error.
\[ MBE = \frac{1}{n} \sum_{i=1}^{n} (T_{p,i} - T_i) \]

\[ RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (T_{p,i} - T_i)^2} \]

\[ Relative\ Error = \frac{1}{n} \frac{|T_{p,i} - T_i|}{T_i} \times 100 \]

\( T_{p,i} \) is the result provided by the ANN, \( T_i \) is the target, and \( n \) is the number of data
Chapter 5 Artificial Neural Network Model Development

5.1 Generation of Training, Validation, and Testing Sets

5.1.1 Reservoir Model

Training, validation and testing data sets for the artificial neural networks are generated by using CMG-IMEX black oil simulator for the model presented in Figure 4-1 with the following characteristics.

❖ 21*21*1-dimensional model
❖ Single phase gas ($S_g = 1$)
❖ Initial water saturation ($S_w = 10^{-12}$)
❖ Well located along the block (11,11,1) as present in Figure 4-2
❖ Well producing until the 1/1/2046

Figure 5-1 Schematic 3D reservoir model
Figure 5-2 Cross Section of the layer \( x=11 \) with well at 90°

The first step consists of using local grid refinement to make the model flexible enough to account for the different well inclination.

Figure 5-3 Schematic of well inclination on reservoir model
Figure 4-2 shows the cross section of the middle of the reservoir with the well in the block (21, 21, 1). Figure 4-4 is a schematic of this cross section.

The well direction is dependent on the section length $L_s$ and height $h$ and can be represented by an angle with the horizontal $\beta$ such as

$$\tan \beta = \frac{h}{L_s}$$

In figure 4-5, the well direction is given by the hypotenuses. Taking into account the relationship between the three variables in this figure, it becomes possible to find each of them when the remaining two are known. In other words, when the angle $\beta$ and height $h$ are provided, it is possible to find the length $L_s$ which correspond to find the dimensions of the block (21, 21,1).

Once the dimensions are known, the reservoir model size description is given and the block is refined to account for the perforations of the well. Two considerations were taken to refine it, its minimum dimension and an equal number of blocks in each direction to maximize the well length. The procedure is clearly presented in the figure 4-6.
In this way, it becomes possible to control the well direction. Table 5-1 shows the different values of tangent, section and well length for angles between 5° and 85°.

**Table 5-1** Section and Well length for different angles

<table>
<thead>
<tr>
<th>(\beta^\circ)</th>
<th>tangent</th>
<th>Section Length (L_s) (ft)</th>
<th>Well length (ft)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>(h=120) ft</td>
<td>(h=450) ft</td>
</tr>
<tr>
<td>5</td>
<td>0.0875</td>
<td>1371.606</td>
<td>1376.846</td>
</tr>
<tr>
<td>10</td>
<td>0.1763</td>
<td>680.554</td>
<td>691.052</td>
</tr>
<tr>
<td>15</td>
<td>0.2679</td>
<td>447.846</td>
<td>463.644</td>
</tr>
<tr>
<td>20</td>
<td>0.3640</td>
<td>329.697</td>
<td>350.857</td>
</tr>
<tr>
<td>25</td>
<td>0.4663</td>
<td>257.341</td>
<td>283.944</td>
</tr>
<tr>
<td>30</td>
<td>0.5774</td>
<td>207.846</td>
<td>240.000</td>
</tr>
<tr>
<td>35</td>
<td>0.7002</td>
<td>171.378</td>
<td>209.214</td>
</tr>
<tr>
<td>40</td>
<td>0.8391</td>
<td>143.010</td>
<td>186.687</td>
</tr>
<tr>
<td>45</td>
<td>1.0000</td>
<td>120.000</td>
<td>169.706</td>
</tr>
<tr>
<td>50</td>
<td>1.1918</td>
<td>100.692</td>
<td>156.649</td>
</tr>
<tr>
<td>55</td>
<td>1.4281</td>
<td>84.025</td>
<td>146.493</td>
</tr>
<tr>
<td>60</td>
<td>1.7321</td>
<td>69.282</td>
<td>138.564</td>
</tr>
<tr>
<td>65</td>
<td>2.1445</td>
<td>55.957</td>
<td>132.405</td>
</tr>
<tr>
<td>70</td>
<td>2.7475</td>
<td>43.676</td>
<td>127.701</td>
</tr>
<tr>
<td>75</td>
<td>3.7321</td>
<td>32.154</td>
<td>124.233</td>
</tr>
<tr>
<td>80</td>
<td>5.6713</td>
<td>21.159</td>
<td>121.851</td>
</tr>
<tr>
<td>85</td>
<td>11.4301</td>
<td>10.499</td>
<td>120.458</td>
</tr>
</tbody>
</table>

Those wide ranges for well lengths depending on the reservoir thickness and the inclination angle suggests that it will not be possible to keep a fix well length for all the networks.
Input angle, $\beta$, total height, $h$ and total length, $L$

Compute $L_s = \frac{h}{\tan \beta}$

Dimension of the reservoir model
First 10 blocks size: $\left(\frac{L - 60}{20}, \frac{L - L_s}{20}, h\right)$

$11^{th}$ block size: $(60, L_s, h)$

Last 10 blocks: $\left(\frac{L - 60}{20}, \frac{L - L_s}{20}, h\right)$

If $\beta = 0^\circ$, $L_s = 0.6 \times L$,

If $\beta = 90^\circ$, $L_s = 60 \text{ ft.}$

Local grid refinement of the $11^{th}$ block (center)
Acceptable block size: 30 ft.

Refinement ratio: $1$ to $\frac{h}{30}$

For angle $>60$, divided into 2 blocks

Perforation along the main diagonal
5.1.2 Data Preparation

The next step consists of preparing the input and output needed to training the ANN. The range of data used is presented in table 4-2 and 4-3. The ranges for the porosity and permeability are defined for double porosity system. The single porosity model information can be found in the appendix.

Table 5-2 Reservoir Properties Ranges

<table>
<thead>
<tr>
<th>Reservoir Parameter</th>
<th>Abbreviations</th>
<th>Reservoir Parameter Range</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Permeability</td>
<td>$k$</td>
<td>0.0001 - 0.01</td>
<td>mD</td>
</tr>
<tr>
<td>Fracture Permeability</td>
<td>$k_f$</td>
<td>0.01 - 1</td>
<td>mD</td>
</tr>
<tr>
<td>Porosity</td>
<td>$\phi$</td>
<td>6 - 20</td>
<td>%</td>
</tr>
<tr>
<td>Fracture Porosity</td>
<td>$\phi_f$</td>
<td>0.1 - 3</td>
<td>%</td>
</tr>
<tr>
<td>Initial Pressure</td>
<td>$P_i$</td>
<td>2000 - 8000</td>
<td>psia</td>
</tr>
<tr>
<td>Temperature</td>
<td>$T_i$</td>
<td>100 - 400</td>
<td>F</td>
</tr>
<tr>
<td>Unit Dimension</td>
<td>L</td>
<td>5000 - 15000</td>
<td>ft</td>
</tr>
<tr>
<td>Thickness</td>
<td>$h$</td>
<td>120 - 450</td>
<td>ft</td>
</tr>
<tr>
<td>Gas Specific Gravity</td>
<td>$S_g$</td>
<td>0.6 - 0.9</td>
<td></td>
</tr>
<tr>
<td>Compressibility of Matrix</td>
<td>$C_m$</td>
<td>9.00E-08 - 1.00E-05</td>
<td>1/psi</td>
</tr>
<tr>
<td>Compressibility of Fracture</td>
<td>$C_f$</td>
<td>1.00E-06 - 1.00E-04</td>
<td>1/psi</td>
</tr>
<tr>
<td>Fracture Spacing</td>
<td>$f_s$</td>
<td>1 - 50</td>
<td>ft</td>
</tr>
</tbody>
</table>

Table 5-3 Operational Parameters

<table>
<thead>
<tr>
<th>Well Design Parameter</th>
<th>Abbreviations</th>
<th>Design Parameter Range</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Specified Pressure</td>
<td>$P_{sp}$</td>
<td>14.7 - 0.5*$P_i$+14.7</td>
<td>psi</td>
</tr>
<tr>
<td>Specified Flow Rate</td>
<td>$q_{sp}$</td>
<td>200 - 30,000</td>
<td>MscfD</td>
</tr>
</tbody>
</table>
5.2 Inverse Artificial Neural Network Predictor for Reservoir Characteristics

There are 152 neural networks that been developed during that study. They are divided into four groups. Each network has a unique well inclination angle, specification (pressure transient data or rate transient data) and either it is a single or double porosity model. Therefore, four groups are labeled, RTA-Single, RTA-Double, PTA Single, and PTA Double.

![Networks Subdivision Diagram]

*Figure 5-3 Networks Subdivision*
5.2.1 **Predictor for Single Porosity Reservoir with Pressure Transient Data**

All the 38 networks created using a single porosity model and the pressure transient data requires the same inputs as presented in Figure 5-4 and the output are in Figure 5-5.

**INPUT**

**Reservoir Data**
- A: Unit Area (acres)
- h: Reservoir Thickness (ft)
- Ti: Temperature (F)
- Pi: Initial Pressure (psia)
- Sg: Gas Specific Gravity

**Well Parameters**
- Specified Gas flow rate (SCF/D)
- Pressure (psia) vs Time (days)

**OUTPUT**
- k: Matrix Permeability
- \( \phi \): Matrix Porosity
- \( C_m \): Matrix Compressibility

*Figure 5-4 Inputs for PTA networks

*Figure 5-5 Outputs for single porosity Networks*
The functional links used differ among networks. The most common are presented in Figure 5-6.

**Figure 5-6** Most common functional links

\[
\text{Functional Links}
\]

**Input:**
- \(A \ast h,\)
- \(A \ast h \ast S_g\)

**Output:**
- \(k \ast h,\)
- \(A \ast h \ast \phi,\)
- \(A \ast h \ast \phi \ast S_g\)
- \(\frac{k}{\phi}\)

**Figure 5-7** Network structure for single porosity networks
5.2.2 **Predictor for Single Porosity Reservoir with Production Rate Transient Data**

All the 38 networks created using a single porosity model and the production rate transient data requires the same inputs as presented in Figure 5-8 and the output are presented in Figure 5-5.

![INPUT](image)

**Figure 5-8** Input for RTA networks
5.2.3 Predictor for Dual-Porosity Reservoir with Pressure Transient Data

All the 38 networks created using a dual porosity model and the pressure transient data requires the same inputs as presented in Figure 5-4 and the output are presented in Figure 5-9.

**OUTPUT**
- $k_m$: Matrix Permeability
- $k_f$: Fracture Permeability
- $\phi$: Matrix Porosity
- $\phi_f$: Fracture Porosity
- $C_m$: Matrix Compressibility
- $C_f$: Fracture Compressibility
- $x_f$: Fracture spacing

**Figure 5-9** Output for Dual Porosity Networks

**Figure 5-10** Network structures for double porosity network
5.2.4 PREDICTOR FOR DUAL-POROSITY RESERVOIR WITH PRODUCTION RATE TRANSIENT DATA

All the 38 networks created using a dual porosity model and the production rate transient data requires the same inputs as presented in Figure 5-8 and the output are presented in Figure 5-9.

There were some modifications made in some of the data during the training process to keep the same order of magnitude such as the logarithmic for large numbers like the gas production rate or the multiplication by $10^8$ or $10^7$ for small numbers like the matrix compressibility. All the networks started the same architecture presented in Figure 5-7 for single porosity model and Figure 5-10 for double porosity mode. Depending on the results of the training adjustment were decided such as adding more neurons, more layers or more functional links or changing the transfer function, or the transfer function.
5.3 **FORWARD ARTIFICIAL NEURAL NETWORK PREDICTOR FOR WELL PRODUCTION AND PRESSURE DATA**

In order to get a better comparison between the predictions provided by both models, 76 additional neural networks were added. They mostly use the results from the previously discusses networks and generate a set of data of pressure or production rate versus time from each type of network then compare then to the original set of data. This additional set of networks will provide the user with a stronger confidence about the predictions obtained.

---

**INPUT**

**Reservoir Data**
- \( A \): Unit Area (acres)
- \( h \): Reservoir Thickness (ft)
- \( T_i \): Temperature (\( ^\circ F \))
- \( P_i \): Initial Pressure (psia)
- \( S_g \): Gas Specific Gravity
- Matrix (and Fracture) permeability (mD)
- Matrix (and Fracture) porosity
- Matrix (and Fracture) compressibility (1/psia)

**Well Parameters**
- Specified Gas flow rate (SCF/D)
- Or
- Specified Sandface pressure (psia)

---

**OUTPUT**

- Pressure (psia) vs Time (days)
- Gas flow rate (SCF/D) vs Time (days)

---

*Figure 5-11 Input for Forward networks*

*Figure 5-12 Output for Forward networks*
5.4 Graphical User Interface

A graphical user interface (GUI) was designed to provide an easy and quick access to each network. The GUI is composed of 3 interfaces, the main window, the window for pressure transient data, and the window for rate transient data.

The main window is presented in Figure 5-13. The user will provide information such as the porosity model, the transient data, and the well inclination. Then the user will be directed toward the interface corresponding to the transient data selected.

![GUI Main window](image)

**Figure 5-13** GUI Main window
If the user selects the pressure transient data, he or she will be directed toward the interface as shown in Figure 5-14. Otherwise, an interface as shown in Figure 5-15 will open.

**Figure 5-14** GUI PTA window
Figure 5-15 GUI RTA window
Chapter 6 RESULTS AND DISCUSSIONS

The results from all the networks are presented in the Appendix. This section will present one result from each, rate transient-single porosity (RTA-single), pressure-transient -single porosity (PTA-single), rate transient-dual porosity (RTA-double) and pressure transient-dual porosity (PTA-double) networks. The training function used for all the networks was the scaled conjugate gradient backpropagation function trainscg. Then a comparison among the different well inclination in term of productivity depending on the reservoir size will be discussed. Last, an approach to confirm the effect of pressure drop due to friction being neglected will be established by finding the optimal well length.

5.1 ARTIFICIAL NEURAL NETWORKS PERFORMANCE

5.1.1 PREDICTOR FOR SINGLE POROSITY RESERVOIR FROM RATE TRANSIENT DATA

The results presented in Figure 6-1 shows that the radial-basis function networks do provide better results for all the rate transient data and single porosity models.
Figure 6-1 Average Relative for Single Porosity Rate Transient Network Models

The highest percent relative error is at 25° for the cascade forward network models. From Figure 6-2, the reservoir property that causes that large error, the matrix porosity, is not predicted quiet well by the cascade forward network.
Figure 6-2 Percent Relative Error for Matrix Porosity Angle 25 for Single Porosity with Rate Transient Data

On the other hand, the Figure 6-3 shows the long-term performance of the model, the mean bias error. The higher MBE can be found at 40 and 45° for the cascade forward networks. The fact that this error is positive shows that the predictions are an overestimate from the exact value. Furthermore, the error from a 25° angle is an overestimate as well.
The root square mean error provided in Figure 6-4. It has a trend similar to MBE which suggests that even in terms of short-performance, the angle 40 and 45° models are less accurate.

Those results raise a question about the difference between the percent relative error and the other performance estimators. One is suggesting that 25° is the least accurate while the other one is suggesting that 40 and 45° are the least ones. The data used for each error test and the calculation involved are different.
Figure 6-4 Root Mean Square Error for Single Porosity with Rate Transient Data Models
5.1.2 PREDICTOR FOR SINGLE POROSITY RESERVOIR FROM PRESSURE TRANSIENT DATA

The predictor for single porosity reservoir with pressure transient data show a more accurate results for the radial basis function network as shown in **Figure 6-5**. The average error for this type of network is below 5% for all the models.

The cascade forward network models’ average errors are below 30%. The highest error appears to be between 70 and 85° angles while the other network seems to have a better accuracy towards 0° and at 90°.

**Figure 6-5** Average Relative for Single Porosity Pressure Transient Network Models
On the other hand, the results provided in Figure 6-6 and Figure 6-7 show a different trend. The mean bias error data suggests that the largest overestimation occurs at 20° for a long-term performance. The root square mean error follows the same trend.
Figure 6-7 Root Mean Square Error for Single Porosity with Pressure Transient Data Models
5.1.3 Predictor for Dual-Porosity Reservoir from Rate Transient Data

The predictor for dual-porosity reservoir from rate transient data has a higher error than the model discussed so far for both types of networks. Figure 6-8 shows the lower average error at 0° and the largest at 75° for the cascade forward networks. Figure 6-9 shows how the error differs for data with low order of magnitude compared to data with higher order of magnitude for the cascade forward network.
If only properties such as the matrix porosity, the fracture permeability and the fracture spacing are taken into account, the error ranges between 10 and 25%. On the other hand, properties such as matrix porosity, fracture permeability, and fracture spacing have an average error between 60 and 120%.

Figure 6-9 Average Error for RTA-double models
5.1.4 Predictor for Dual-Porosity Reservoir from Pressure Transient Data

**Figure 6-10** Average Relative for Double Porosity- Pressure Transient Network Models

The predictor for dual-porosity reservoir from pressure transient data has the highest average error for the cascade forward network models. **Figure 6-10** shows the lowest average error at 40° and the largest at 50° for the cascade forward networks. **Figure 6-11** shows how the error differs for data with low order of magnitude compared to data with higher order of magnitude for the cascade forward network.
If only properties such as the matrix porosity, the fracture permeability and the fracture spacing are taken into account, the error ranges between 17 and 30%. On the other hand, properties such as matrix porosity, fracture permeability, and fracture spacing have an average error between 65 and 100%.

The results presented in sections Chapter 0 show that the radial basis function network models provide a better estimate than the cascade forward network models. However, at the beginning of the study, the 40 years of production and pressure data were all accounted for which produced a total of more than 300 inputs and the radial basis function showed some limitations and poor accuracy. After
simplification by considering average of production and pressure that reduced the number of inputs to 100 or less, the radial basis function showed better results. Also, the training for models with angles between 20 and 70° has showed to take a longer time to reach the accuracy provided for both type of networks. Those systems have longer well lengths and more complex structures.

Figure 6-12. GUI Main Window
Some improvement made in the Graphical User Interface. The main window, Figure 6-12, is the same. If pressure transient data is selected, the window presented in Figure 6-13 opens up. An option to import all the inputs from a text file was added to the GUI. The data have to follow a certain order in the text file. First, the reservoir data, in the order presented in the GUI, then the well specified flow rate and the pressure transient data with time.

![Figure 6-13 Pressure Transient Data GUI Window](image)

Once the GUI is run, the results appear as in Figure 6-14
Another option is to save those results along with the inputs and network information in a text file, Figure 6-15. The last option is the possibility to compare the results with the exact value or another approximation if available. Again, the order presented in the window above for the results should be considered as presented in Figure 6-16.
63

NETWORK NAME: PTA_D_deg30

NETWORK DESCRIPTION
Porosity Model: Double
Pressure Transient Data
Angle (degree): 30

<table>
<thead>
<tr>
<th>NETWORK TYPE</th>
<th>Cascade Forward Backpropagation</th>
<th>Radial Basis Function</th>
</tr>
</thead>
</table>

RESULTS
Matrix Porosity 1.403810e-01 1.433900e-01
Fracture Porosity 1.270310e-02 8.157650e-03
Matrix Permeability (mD) 4.715640e-02 6.580410e-02
Fracture Permeability (mD) 4.834360e+00 2.643550e+00
Matrix Compressibility (l/psi) 4.031500e-06 4.685820e-06
Fracture Compressibility (l/psi) 3.729520e-05 6.749210e-05
Fracture Spacing (ft) 3.046000e+01 2.251810e+01

Figure 6-15. Saved Results from the GUI

![Gas Flow Rate vs Time](image)

Figure 6-16. Comparison of Results.
5.2 Well Direction Recommendation

In a single porosity system and a large reservoir, a horizontal well is recommended as shown in Figure 6-17. The reservoir has about 5000 acres and 360 ft. thickness. The plot suggests that at the end of 12,000 days, the boundaries of the reservoir have not been felt yet. In fact, Figure 6-18 presents the different well length for this case and it should be reminded that besides the horizontal well whose length depends on the reservoir unit dimension, approximately 60% of it, the maximum depends on the thickness and the inclination angle.

![Cumulative Gas Production vs time](image)

**Figure 6-17** Production Comparison in a Single Porosity System
Moreover, a plot at the productivity per unit length of the well will provide a single line throughout because the timeframe is during early times.
Figure 6-19 Production Comparison in a Dual Porosity System

In Figure 6-19 shows a completely different trend in a dual porosity system. The effect of the boundaries becomes noticeable. In this case as well, the horizontal well provides the best output. In that case, however, if we plot the production per unit length, we observe a common line for the first 4000 days then an opposite trend where the horizontal well provides a lower production compare to everybody. In this case, there are a lot of factors that can caused that such as the drainage area respective to each configuration, and effects due to superposition of each unit length. The horizontal well will have the smallest drainage are if compared to the vertical well and is longer than any other well. Once the transient line from each unit length reaches the boundary, it decreases the pressure and the effect of the
surrounding well section will create a larger pressure drop which therefore will decrease the production more quickly for each unit length.

**Figure 6-20** Production Comparison in a Single Porosity System (small reservoir)

*Figure 6-20* shows the production for a single porosity system in a smaller reservoir. In this case as well, a horizontal well is recommended. As expected, with the reservoir being smaller, the boundary will be felt quite faster.
Figure 6-21 Production Comparison in a Dual Porosity System (small reservoir)

Figure 6-21 presents the production in a dual porosity for a small reservoir. In this case, early time is even smaller mainly due to large fracture permeability. In this case as well, the horizontal well provides the best production.
5.3 OPTIMUM WELL LENGTH

Now that it has been establish that the horizontal well length was the best option for any case scenario, it would be important to determine the effect that the well length has on production. In fact, from the literature it is suggested that beyond a certain well length, the effect of friction cannot be neglected.

![Cumulative Gas Production (SCF)](image)

**Figure 6-22** Cumulative Production with different Well Length

By looking at the specific case of single porosity system as described in the previous section, we can see from **Figure 6-22** that the horizontal well is production less below and above 9000 ft. This length is the optimal length that should be
considered when drilling a horizontal well in a reservoir with the specification described earlier.

In general, there is always a maximum length that would justify the expenditure when other factors such as the cost of drilling are accounted for.
Chapter 7 SUMMARY AND CONCLUSIONS

This study proposes a neural network tool for a single gas phase reservoir with a slanted well. Local grid refinement was used to design the reservoir models. The tool considers two type of porosity models, and can make prediction when rate transient data or pressure transient data are available. Furthermore, it provides results from two types of network, cascade forward backpropagation and radial basis function. With all those options, a total of 152 networks were trained and combined into one GUI.

Cascade forward backpropagation provides a less better accuracy than radial basis function for all the networks. However, when exposed to a completely different dataset, both estimates were not so far off and the cascade forward backpropagation gave a better result than the radial basis function for some of the properties.

Artificial Neural Network, once again proved that it is possible to obtain accurate results in a timely manner. The training process is continuous, it is still possible to obtain better results. The radial basis function network has shown a strong and reliable and less time consuming to train when coupled with the scaled gradient conjugate training algorithm.

Horizontal wells are preferable in most cases. Also, in order to neglect the effect of friction an optimum well length should be consider.
REFERENCES


APPENDIX

APPENDIX A PARAMETER DISTRIBUTION

Matrix Porosity Distribution

Fracture Porosity Distribution
APPENDIX B MATLAB CODE

Local grid refinement script 1 (Initialization)

The reservoir and local grid(section) division based on the well inclination.

```matlab
n=500;
angle=0:5:90;
base=importdata('indata.txt');
for jj=1:19
    ang=angle(jj);
    for i=1:n
        h=base(2,i); % Reservoir Thickness
        L=base(1,i); % Reservoir Unit Dimension
        refz=h/30;
        if ang>0&&ang<90
            tanfac=tan(ang*pi/180);
            maxL=h/tanfac;
            wellmax=sqrt(maxL^2+h^2);
            refy=refz;
            if ang>60
                refy=2;
                refz=2;
            end
        end
        dy2=maxL;
    end
end
if ang==0
    wellmax=0.6*L;
    dy2=wellmax;
    refy=20;
```
%%for 90 degree angle, vertical well, the section length is the thickness

elseif ang==90

    wellmax=h;
dy2=wellmax;
    refy=6;
end

dx1=(L-60)/20; % compute each gridblock size in the x-direction left when section is removed
dy1=(L-dy2)/20; % compute each gridblock size in the y-direction left when section is removed.

%Save all the data
    table(1,i)=dx1;
    table(2,i)=dy1;
    table(3,i)=dy2;
    table(5,i)=refy;
    table(6,i)=refz;
end

%Save file for each angle
    FileName=['ref',num2str(ang),'.txt'];
save(FileName, 'table', '-ascii')
end
Local grid refinement script 2 (Perforation Data)

Script to store the well perforation location in the locally refined section.

Well perforation along the diagonal of the section for inclination between 0 and 90°.

```matlab
clear
ang=0:5:90;
base=importdata('indata.txt');
n=500;
for jj=1:length(ang)
clear table%start a new table
angle=ang(jj);
hh=1;
%retrieve data from script 1
filename=['ref',num2str(angle),'.txt'];
datas=importdata(filename);
for ii=1:n
    numx=21;%number of block in the x direction
    H=base(2,ii);%the reservoir thickness
    L=base(1,ii);%the unit dimension length
    numy=21;%number of block in the y direction
    refy=datas(5,ii);%number of blocks in the section (y-direction)
    refz=datas(6,ii);%number of blocks in the section (z-direction)
    %Format preparation for CMG (local grid refinement)
    x_track=11;%Location of section in the x direction
    y_track=11;%Location of section in the y direction
    h_track=1;%Location of section in the z direction
    y=refy;
    h=refz;
    %Perforation Tracker
    if angle==0
        % for angle 0, only moving along the y-direction in the middle of the z-direction
        for iii=1:refy
            table(iii,hh)=x_track;%x location in the global grid
            table(iii,hh+1)=y_track;%y location in the global grid
            table(iii,hh+2)=h_track;%z location in the global grid
            table(iii,hh+3)=1;%x location in the local grid
            table(iii,hh+4)=y;%y location in the local grid
            table(iii,hh+5)=h/2;%z location in the local grid
            y=y-1;
        end
    elseif angle==90
```
elseif angle == 90
  \%\% for angle 90, only moving along the z-direction in the middle of the y-direction
  for iii = 1 : refz - 1
    table(iii, hh) = x_track;
    table(iii, hh + 1) = y_track;
    table(iii, hh + 2) = h_track;
    table(iii, hh + 3) = 1;
    table(iii, hh + 4) = y / 2;
    table(iii, hh + 5) = iii + 1;
  end
end
else
  \%\% for other angles, moving in both direction
  for iii = 1 : refz - 1
    table(iii, hh) = x_track;
    table(iii, hh + 1) = y_track;
    table(iii, hh + 2) = h_track;
    table(iii, hh + 3) = 1;
    table(iii, hh + 4) = y - iii;
    table(iii, hh + 5) = iii + 1;
  end
end
hh = hh + 6;
end
\%\% save the perforation direction
FileName = ['perf', num2str(angle), '.txt'];
save(FileName, 'table', '-ascii')
end
CMG Data Files Generator

Sections containing local grid refinement and well perforation as well as a required line to output pressure data for PTA

```matlab
%% Inputs for this code
load indata.txt
count=0;
%Network Description
SINGLE=1;%single porosity model if SINGLE=1, DUAL for others
RTA=1;%Rate transient Data if RTA=1, Pressure Transient data for others
angle=0;
%Load the refinement information
refsfilename=['ref',num2str(angle),'.txt'];
refs=importdata(refsfilename);
%load the perforation information
perfsfilename=['perf',num2str(angle),'.txt'];
perfs=importdata(perfsfilename);
%% Printing CMG files
forCMG=('CMGBATCH.bat');
fidbat=fopen(forCMG,'wt');
for i=1:length(indata(1,:));
    numb= num2str(i');
    temp=['data' numb '.dat'];
    fid=fopen(temp,'wt');
    for i=1:length(indata(1,:));
        numb= num2str(i');
        temp=['data' numb '.dat'];
        fid=fopen(temp,'wt');
        fprintf(fid, \n RESULTS SIMULATOR IMEX 201401 ');
        fprintf(fid, \n )
        fprintf(fid, \n )
        fprintf(fid, \n )
        fprintf(fid, \n )
        fprintf(fid, \n INUNIT FIELD ');
        fprintf(fid, \n WSRF WELL 1 ');
        fprintf(fid, \n WSRF GRID TIME ');
        fprintf(fid, \n WSRF SECTOR TIME ');
        fprintf(fid, \n OUTSRF WELL LAYER NONE ');
        fprintf(fid, \n OUTSRF RES ALL ');
        fprintf(fid, \n OUTSRF GRID SO SG SW PRES OILPOT BPP SSPRES WINFLUX ');
        fprintf(fid, \n *OUTSRF *SPECIAL 11 11 1 PRES');
        fprintf(fid, \n WPRN GRID 0 ');
        fprintf(fid, \n OUTPRN GRID NONE ');
```
fprintf(fid,\n **
***************************************************************************
**
\nGRID    VARI    21 21 1 ')
\nKDIR    DOWN                                    '
\nDI  IVAR                                    '
\n10*%d',refs(1,i))
\n1*%d',60);
\n10*%d',refs(1,i))
\nDVAR    ')
\n10*%d',refs(2,i)    );
\n1*%d',refs(3,i));
\n10*%d',refs(2,i));
\n441*%d',indata(2,i)    );
\n441*0'    );
\n*REFINE 1 %d',refs(5,i));
\n% d ',refs(6,i)));
\n*RANGE 11:11 11:11 1:1 '});
\n'};
fprintf(fid,'\n INITIAL                     ');
fprintf(fid,'\n USER_INPUT                  ');
fprintf(fid,'\n PRES    CON %d',indata(7,i)  );
fprintf(fid,'\n SW CON 1.00E-12             ');
fprintf(fid,'\n NUMERICAL                  ');
fprintf(fid,'\n RUN                         ');
fprintf(fid,'\n DATE  2016  1  1               ');
fprintf(fid,'\n **                                      ');
fprintf(fid,'\n WELL    "Well-1"                  ');
fprintf(fid,'\n PRODUCER    "Well-1"               ');
if RTA==1
  fprintf(fid,'\n OPERATE  MIN  BHP %d',indata(13,i));
else
  fprintf(fid,'\n OPERATE  MAX STG %d',indata(14,i));
end
fprintf(fid,' CONT');
fprintf(fid,'\n **  UBA ff  Status  Connection                  ');
fprintf(fid,'\n **  UBA ff  Status  Connection                  ');
fprintf(fid,'\n **  rad geofac  wfrac   skin                      ');
fprintf(fid,'\n GEOMETRY    K   0.25    0.37    1   0                   ');
fprintf(fid,'\n PERF    GEOA    "Well-1"                         ');
fprintf(fid,'\n **  UBA ff  Status  Connection                 ');
fprintf(fid,'\n 11 11 1 / 1   %d ');
fprintf(fid,' / %d ',perfs(1,count+5));
fprintf(fid,' 1  1.0    OPEN  FLOW-TO "SURFACE"   ');        
for cc=1:nnz(perfs(:,count+1))
  fprintf(fid,'\n %d',perfs(cc,count+1));
  fprintf(fid,' %d',perfs(cc,count+2));
  fprintf(fid,' / %d',perfs(cc,count+3));
  fprintf(fid,' / %d',perfs(cc,count+4));
  fprintf(fid,' / %d',perfs(cc,count+5));
  fprintf(fid,' / %d',perfs(cc,count+6));
end
fprintf(fid,' 1.0    OPEN  FLOW-TO %d',cc );
end
count=count+6;
### APPENDIX C ANN TOOL STRUCTURES

<table>
<thead>
<tr>
<th>Net #</th>
<th>Network Name</th>
<th>Network type</th>
<th>Average Error (%)</th>
<th>$R^2$</th>
<th>MBE</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0-RTA-SINGLE</td>
<td>Cascade forward</td>
<td>10.025</td>
<td>0.928</td>
<td>-0.009</td>
<td>0.072</td>
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<tr>
<td>2</td>
<td>5-RTA-SINGLE</td>
<td>Radial-Basis</td>
<td>1.730</td>
<td>0.996</td>
<td>0.013</td>
<td>0.095</td>
</tr>
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<td>3</td>
<td>10-RTA-SINGLE</td>
<td>Cascade forward</td>
<td>9.165</td>
<td>0.936</td>
<td>0.059</td>
<td>0.388</td>
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<tr>
<td>4</td>
<td>15-RTA-SINGLE</td>
<td>Radial-Basis</td>
<td>1.576</td>
<td>0.994</td>
<td>0.007</td>
<td>0.044</td>
</tr>
<tr>
<td>5</td>
<td>20-RTA-SINGLE</td>
<td>Cascade forward</td>
<td>9.888</td>
<td>0.912</td>
<td>0.029</td>
<td>0.199</td>
</tr>
<tr>
<td>6</td>
<td>25-RTA-SINGLE</td>
<td>Radial-Basis</td>
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<td>0.995</td>
<td>-0.001</td>
<td>0.005</td>
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<tr>
<td>7</td>
<td>30-RTA-SINGLE</td>
<td>Cascade forward</td>
<td>11.124</td>
<td>0.919</td>
<td>0.031</td>
<td>0.226</td>
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<tr>
<td>8</td>
<td>35-RTA-SINGLE</td>
<td>Radial-Basis</td>
<td>1.730</td>
<td>0.996</td>
<td>-0.002</td>
<td>0.019</td>
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<tr>
<td>9</td>
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<td>0.142</td>
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<tr>
<td>10</td>
<td>45-RTA-SINGLE</td>
<td>Radial-Basis</td>
<td>1.630</td>
<td>0.994</td>
<td>-0.012</td>
<td>0.082</td>
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<tr>
<td>Net #</td>
<td>Network Name</td>
<td>Network type</td>
<td>Average Error (%)</td>
<td>$R^2$</td>
<td>MBE</td>
<td>RMSE</td>
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<tr>
<td>31</td>
<td>75-RTA-SINGLE</td>
<td>Cascade forward</td>
<td>12.310</td>
<td>0.925</td>
<td>0.034</td>
<td>0.250</td>
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<tr>
<td>32</td>
<td>Radial-Basis</td>
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<td>0.043</td>
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