The Pennsylvania State University

the Graduate School

Department of Energy and Mineral Engineering

ARTIFICIAL NEURAL NETWORK BASED DESIGN FOR DUAL LATERAL WELL APPLICATIONS

Thesis in

Energy and Mineral Engineering

by

Khaled Enab

Submitted in Partial Fulfillment

of the Requirements

for the Degree of

Master of Science

August 2012

The thesis of Khaled Enab was reviewed and approved* by the following:

Turgay Ertekin
Professor of Petroleum and Natural Gas Engineering
George E. Trimble in Earth and Mineral Sciences
Thesis Advisor

Luis F. Ayala H.
Associate Professor of Petroleum and Natural Gas Engineering

John Yilin Wang
Assistant Professor of Petroleum and Natural Gas Engineering

R. Larry Grayson
Professor of Energy and Mineral Engineering
Graduate Program Officer of Energy and Mineral Engineering;

*Signatures are on file in the Graduate School

ABSTRACT

Artificial neural networks (ANNs) have become an important tool for the petroleum industry, for performance analysis of reservoirs, because their ability of understanding highly non-linear relationships and its capacity to perform simulation studies in a rapid manner.

Artificial neural networks is a computational tool that is based on the way that the brain performs computations as it depends on knowledge based training strategies to build an experience in predicting the results of problem within the range of the trained cases.

Since the increased use of natural gas all over the world, it has become more important to increase the gas production worldwide. Accordingly, many efforts have been expended to improve the production techniques such as using the multi-lateral wells which are capable to accomplish higher production rates.

Determining the cumulative gas recovery profile, is an important step in the gas production characteristics, which presents the recovery performance through the well-life time which helps in detecting the well life-time and the revenue that can be realized after the detected well-life time.

Using the multi-lateral wells technique leads to increase the cumulative fluid recovery, decreases the environmental impacts and decreases the cost of drilling and completion.

The neural network developed in this study is able to predict the cumulative gas recovery profile from a tight shale gas reservoir with a multi-lateral well (dual horizontal well completion).

In this study two artificial neural networks have been developed to achieve two main objectives. The forward ANN has been developed to predict the gas recovery profile for a chosen dual horizontal well configuration over a specified production period. The inverse ANN has been developed to determine a dual horizontal well design that can be used to achieve a desired gas recovery over a specified production period.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGEMENTS

I would like to express my sincere gratitude and appreciation to my advisor and mentor Prof. Turgay Ertekin for his support, help, encouragement, patience and guidance during my work in my thesis. Also, I would like to extend my gratitude to my committee members Dr. Luis Ayala, Dr. John Yilin Wang.

Also I would like to thank my colleagues Talal Alamosa, Hussam Alshraideh and Mohamed Al-Rumah for their help, support, encouragement, and great friendship.

I am indebted to my father Dr. Ahmed Enab, my mother Mrs. Enab and my brothers for being the endless source of support and encouragement. I would also like to thank my wife Ghada for her help and encouragement.

Finally, my love to my little daughter Salma

Chapter 1

INTRODUCTION

Artificial neural network is a mathematical model which mimics the structure and the function of the biological neural networks. In addition, artificial neural network is a non-linear statistical data modeling system which is used to identify the existing complex relationships between the inputs and the outputs. An artificial neural network is an adaptive system which consists of interconnected artificial neurons. The network explains the desired relationships based on the way of connecting these neurons. The artificial neural network adapts its structure depending on the internal and external data, which are used in the network during the training and learning process, in order to build a network which gives the best identification for the desired relationship.

The present study has been conducted to generate two different neural networks. The first network predicts the cumulative gas production and the recovered amount of gas in place by the dual lateral well. The second network predicts the dual lateral well design that can be used to achieve a desired gas recovery within a specified period of time. These two networks can help in predicting the well configuration that can be used to maximize the gas recovery, as well as comparing the gas recovery for different well configurations in a rapid fashion.

Chapter 2

LITERATURE SURVEY

2.1. MULTI LATERAL WELLS

The multilateral well application is a relatively new technology which has been utilized to increase the rate of recovery from a reservoir with comparably lower drilling expenses.

i. Introduction

Multilateral well can be described as two or more wellbore branches which connected to a single surface main borehole. Drilling a multilateral well is built on the directional drilling technology. The first step of drilling a multilateral well is drilling vertically cross the reservoir bedding plane. The second step is drilling the horizontal branch by drilling horizontally parallel to the reservoir bedding plane at a specified depth. The second step can be repeated depending on the selected multilateral well design. There are many types of multilateral wells like multi-branched well, forked well, laterals into horizontal hole, laterals into vertical hole, stacked laterals and dual-opposing laterals (Joshi, 2007). Selecting the type of the multilateral well depends on the reservoir conditions and properties.

The selected well for this study is a dual horizontal well which consists of two horizontal holes connected to a single surface hole with different phase angels between the horizontal branches and with changing vertical distances between the branches.

The first multilateral well, was drilled in 1953, was an oil well called 66/45. This well was drilled in the Bashkiria field near Bashkortostan, Russia (Bosworth et al, 1998). This well had nine laterals branches which connected to a single borehole (Bosworth et al, 1998). This nine lateral well has increased the contact area between the well and the reservoir by 5.5 times and the production by 17-fold, yet drilling this well cost only 1.5 times of that the conventional well would have cost (Bosworth et al, 1998).

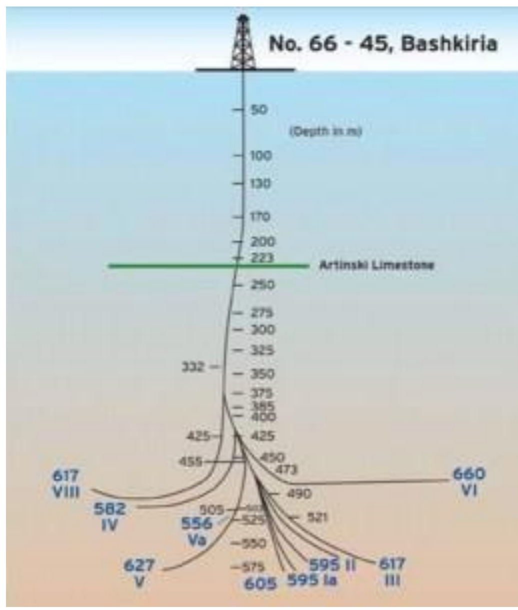


Figure (2.1): The first multilateral well (66/45), From Reference (Bosworth et al, 1998)

Between 1980 and 1995, the multilateral well technology was rather new and only 45 wells have been drilled. After 1995 hundreds of multilateral wells have been drilled because of the rapid development of the directional drilling techniques (Bosworth et al, 1998).

ii. Benefits of a Multilateral Well

- Increasing the rate of recovery

  Using multilateral wells application increases the production rate by three to five times as using the horizontal well increases the contact area between the well and the reservoir (Joshi, 2007). The reservoir production used to be expanded by drilling more wells to increase draining and sweep efficiency. By using the multilateral wells, the production will be expanded by drilling one well which is capable of contacting more reservoir surface than the conventional well.

- Decreasing the drilling expenses

  Drilling multilateral well increasing the rate of recovery by three to five times and the drilling cost by 1.5 to 2 times (Joshi, 2007).

- Decreasing the environmental impact

  Using the multilateral well decreases the environmental impact as the multilateral well needs a single surface borehole instead of many boreholes, to cover the same reservoir contact area, if any other technique has been used.

- Accelerating production

  Using the multilateral well application saves significant amount of time compared to other techniques as it will:

  I. effectively accelerate the production.

  II. rapidly deplete the reservoir.

  III. reduce the operating costs as the field life cycle shortened.

2.2. ARTIFICIAL NEURAL NETWORKS

An artificial neural network is a mathematical model which mimics the structure and the function of the biological neural networks. In addition, artificial neural network is a non-linear statistical data modeling system which is used to identify the existing complex relationships between the inputs and the outputs. The artificial neural network is an adaptive system which consists of interconnected artificial neurons. The network explains the desired relationships based on the way of connecting these neurons. The artificial neural network adapts its structure depending on the internal and external data, which are used in the network during the training and learning processes, in order to build a network which gives the best identification for the desired relationship.

Training the artificial neural network starts by dividing the available data to three sets training, testing and validation. The first set is the training set which the ANN trains in order to build an intelligent knowledge field that explains the relationship between the inputs and outputs. After trying many connections between the neurons and changing the weights of the inputs, the ANN selects the best network which gives the best explanation of the problem under consideration. The second step is testing the selected network by using inputs from a fresh set of data and compares its output to the network output. These two steps are repeated more and more until reaching the most satisfactory results.

In 1950's Rosenblatt generated the first artificial neural network. This network generates a weight vector in a finite number of training sessions in order to build a relation between the input and the output (Mohaghegh, 2000). Rosenblatt has tried to generate a structure with more layers to remove the limitation of his first network but there were no learning algorithms could help him in achieving his goal.

After 20 years, Hopfield developed new learning algorithms which opened the way for many researchers to develop the artificial neural networks. The back-propagation algorithm, which has been used in this study, was one of these more recent algorithms (Mohaghegh, 2000).

2.2.1. ANNs IN PETROLEUM ENGINEERING

Artificial neural network is a useful tool for the petroleum engineering applications because of the number of uncertain and unknown variables which prevent solving many problems by the conventional methods. Also, ANN is helping to solve the complicated problems in terms of their time requirements and the problems which are impossible to solve by using the conventional methods (Mohaghegh, 2000).

Artificial neural networks have been used in the oil and gas field for many years. Artificial neural network's supervised training algorithms are the most commonly used ones in the oil and gas industry because of their accuracy in solving many challenging and complex problems in the oil and gas industry (Ramgulam, 2007). ANNs have been used in predicting the formation characteristics such as permeability, porosity and water saturation (Basbug, 2007), (Giller, 1999). In addition, ANNs have been used in predicting the reserve production rate where a reservoir simulation has been used to generate the required data to train and test the neural network (Srinivasan, 2008).

Chapter 3

GENERATING DATA USING COMPUTER MODELING GROUP (CMG)

The first step to design an artificial neural network is to generate a trusted database which covers the selected range for the study. CMG* commercial reservoir simulation software is utilized to generate the required data for this study.

3.1 RESERVOIR PROPERTIES' RANGE

The initial step to prepare the required data for training the simulator is determining the properties which affect the recovered amount of gas in place. The parameters which affect the gas recovery are the reservoir fluid characteristics and the characteristics of the relative reservoir rock properties (Gentry & McCray 1987). These characteristics are permeability, porosity, compressibility, thickness, depth, initial pressure and temperature. The reservoir properties' range selected for this study is shown in the Table (3.1).

Table (3.1) Reservoir properties range covered in the study

Property	**Minimum**	**Maximum**
Vertical permeability	0.0001 md	0.1 md
Horizontal permeability	0.001 md	1 md
Porosity	0.06	0.25
Compressibility	1.00E-08	1.00E-06
Thickness	50 ft.	500 ft.
Depth	2000 ft.	8000 ft.
Pressure	2000 psi	8000 psi
Temperature	100^{0} F	300^{0} F
Gas gravity	0.5	0.7
Pattern size	27 Acre	2700 Acre

* Computer Modeling Group (CMG)
#200, 1824 Crowchild Trail N.W.
Calgary, Alberta, Canada T2M 3Y7

3.2 PREPARING INPUT DATA FOR THE SIMULATOR

In order to cover the selected reservoir properties' range, a number of cases have been generated with a different reservoir properties combination. Matlab code has been utilized to generate random reservoir properties combinations within the selected limits of the reservoir properties. In order to avoid any outstanding reservoir properties combinations, there are some constrains have been considered while generating the random properties combinations such as;

- The relationship between the well vertical distances and the thickness
- The relationship between the well horizontal lengths and the pattern size.
- The relationship between the depth of the reservoir, the pressure and temperature.

The bottom hole pressure has been specified at 500 psi as it can provide a general overview about the well if a higher or lower bottom hole pressure specified. 500 psi is more practical bottom hole pressure because it avoid producing junk out of the well, if a low bottom hole pressure specified. As well using a low bottom hole pressure requires compress the gas into the pipelines at the surface.

Three sets of data have been developed; every single set covers the selected range for the study. The three sets were generated as followed;

- 80% of the cases for training the ANN
- 10% of the cases to validate the ANN
- 10% of the cases for testing the ANN

3.3 THE SIMULATOR DATA FILES

Generating the data files for the simulator is the initial step in predicting the gas cumulative production and the recovered amount of the gas in place.

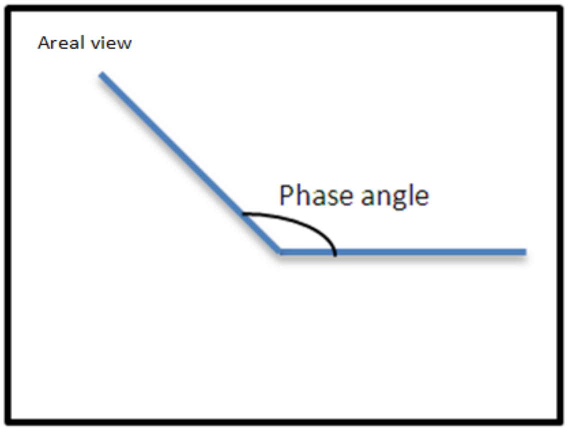
The first part of the data file is a description for the studied reservoir. The data file starts with defining the reservoir grid system and the size of the pattern. In this study a three dimensional Cartesian grid system with 1331 blocks (11*11*11) has been used. Every single reservoir has different pattern size within the selected range. The second part of the data file identifies the reservoir properties such as permeability, porosity, rock compressibility, depth of the reservoir, reservoir thickness, pressure and temperature.

The third part of the data file contains two tables. The first table describes the relationship between the pressure, compressibility factor and the viscosity. The second table describes the relationship between the permeability and the gas saturation.

The last part of the data file identifies the perforation of the wells and the bottom hole pressure. The selected bottom hole pressure for this study is 500 psi. A dual horizontal producer well has been chosen for this study. The two horizontal wells start at the center of the reservoir at different vertical distances from the top of the reservoir.

There are five well configuration parameters that need to be determined in order to determine the well penetration inputs which are;

- The vertical distance from the top of the reservoir to the first horizontal well.
- The vertical distance from the top of the reservoir to the second horizontal well.
- The first horizontal well length
- The second horizontal well length
- The phase angle which is the angle between the two horizontal branches.



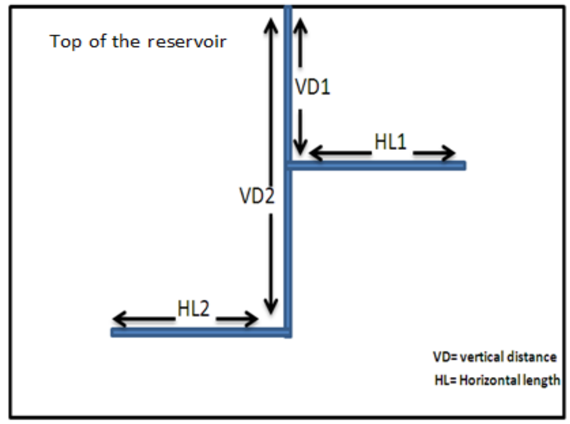


Figure (3.1): (a) Reservoir areal view **(b) Reservoir sectional view**

After specifying the rock properties, fluid properties, initial condition (pressure, temperature and saturation) and the well perforation, a time step has been selected to cover 50 years of production. There are 18 different times in a chronological order that have been selected to present the cumulative production profile and the gas recovery profile. A sample of data files is given in the Appendix (H).

3.4 GENERATING DATA FILES

Generating the data files is the last step to prepare the required data for training the artificial neural network. Data files correspond to the required information to the simulator which helps in generating the gas cumulative production. This information, as mentioned before are permeability, porosity, rock compressibility, thickness, depth, initial pressure, temperature, gas gravity, vertical separations, horizontal lengths and phase angle. When all the data files generated, a batch file containing all the data files will run by the commercial simulator generating the output. This study focuses at the effect of using the dual horizontal well on the cumulative production and the gas recovery profile over the time.

A MATLAB* code has been utilized to extract the cumulative production and the gas rate at the end of the simulation and save it to matrix named ‘output’. Another matrix called ‘input’ is saved which contains the permeability, porosity, rock compressibility, thickness, depth, initial pressure, temperature, gas gravity, vertical separations, horizontal lengths and phase angle.

The reservoir simulator does not produce the recovery profile versus time. The Matlab code used to calculate the recovery profile versus time by dividing the cumulative gas production by the gas in place and save it to matrix named ‘recovery’. After generating ‘input’ and ‘recovery’ matrices, all the required data for creating the intelligent system are ready.

**MATLAB is a programming environment for algorithm development, data analysis, visualization, and numerical computation.*
The MathWorks, Inc.
3 Apple Hill Drive, Natick, Massachusetts 01760 USA

Chapter 4

NEURAL NETWORK DESIGN

There are a number of design parameters that has to be considered in designing a neural network such as the neural network architecture, number of hidden layers, transfer function, training function, learning rule and error calculation.

4.1 ARCHITECTURE

Selecting the neural network architecture is the first step in building the neural network. The neural network architecture determines the method of connecting the weights at the network and defines the used learning rule in the network. The multilayer feed-forward is the selected architecture for this study as it is the most commonly used architecture in the engineering field and recommended for most applications (Demuth et al, 2009). A feed-forward protocol is built to connect inputs to outputs by one way to help in predicting the best nonlinear function fitting (Demuth et al, 2009). There are number of networks which support the feed-forward like feed-forward back-propagation and cascade-forward back-propagation. In this study feed-forward back-propagation and cascade-forward back-propagation has been trained. Feed-forward back-propagation has been selected because of its better fitting for the selected data.

4.2 LEARNING ALGORITHM

Selecting the learning algorithm is an important step because it adjusts the weights through the training to decrease the errors rapidly. The most common learning algorithm is the back-propagation which has been selected as a learning algorithm for this study. There are different types of back-propagation algorithms. After training with different types of algorithms, conjugate gradient algorithm is selected as a learning algorithm for this study because it gave the best performance, input/output relation, in shorter time.

4.3 BACK-PROPAGATION

Back-propagation is a nonlinear differential transfer function. Input vector and related output vector prepared to be trained by back-propagation algorithm in order to achieve the function which gives the best description for the relation between the inputs and the outputs (Demuth et al, 2009). The used data, inputs and related outputs, have to be divided to three groups. The first group is for the training, the second group is for the validation and the third group is for the testing.

Figure (4.1) shows the architecture of the feed-forward back-propagation. It contains three major layers input layer, hidden layer and output layer. Each layer consists of a number of elements or neurons. The input layer consists of the selected parameters which are used to predict the desired output parameters. The number of the neurons in the input and output layers depends on the selected data. The hidden layers consist of a number of neurons which can be selected by the trial and error method. In order to select the number of hidden layers and the number of the neurons in each layer only one hidden layer with a number of neurons equal to the number of the output parameters was selected as a beginning. Then, the number of the neurons is increased until the network achieves the best performance. The third step is increasing the number of the hidden layers and the neurons in each layer until a satisfactory performance is achieved.

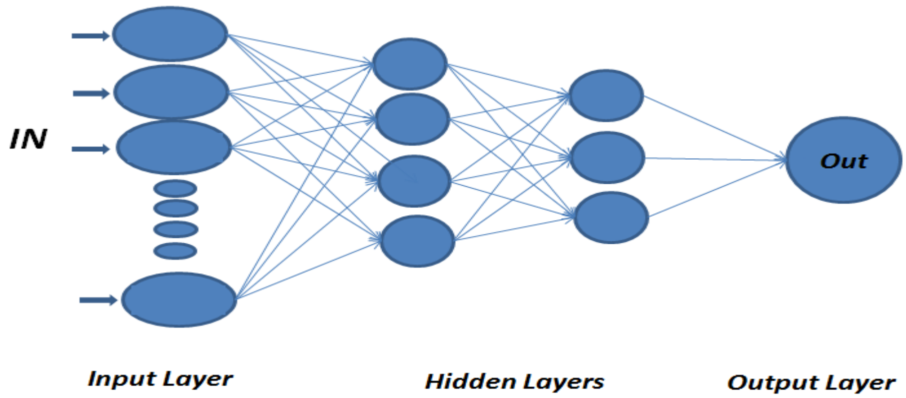


Figure (4.1): A typical neural network architecture

4.4 TRANSFER FUNCTION

The transfer function is the function which is responsible for generating the output from the weighted inputs. The weights are determined by the learning algorithm, before the input vectors are connected to generate the network weighted input. The transfer function uses this network weighted input to generate the output.

There are many transfer functions while the most commonly used one is the *sigmoid* function which contains *tan sigmoid* and *log sigmoid*. After training different transfer functions, *tan sigmoid* has been selected for this study because it gave the best performance for the selected problem. *Tan sigmoid* takes the input vector and compresses the output into the range of -1 to 1 (Demuth et al, 2009).

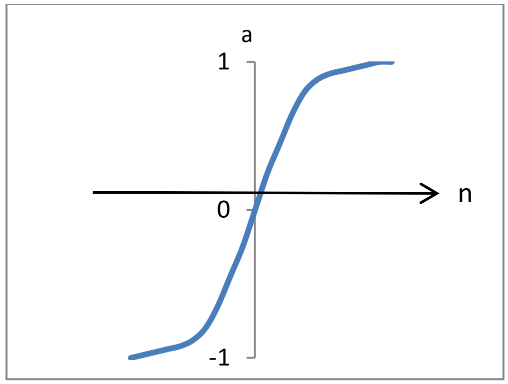


Figure (4.2): ***tan sigmoid*** **transfer function [a =** ***tansig*** **(n)]**

4.5 ERROR CALCULATION

The mean square error (MSE) is the selected error calculation function for this study. Mean square error is calculating the average of the error between the network's output and the target output over all studied pairs (Demuth et al, 2009).

Chapter 5

FORWARD NETWORK DEVELOPMENT

The forward network has been generated to predict the recovery profile for a selected dual horizontal well configuration at specified reservoir properties over a time period of 50 years. The well produces at 500 psi bottom hole pressure. The goal of the forward network is to guide the user before drilling a dual horizontal well by predicting the gas recovery, gas rate and cumulative production for a time period of 50 years. The input parameters for the forward network are displayed in the following table.

Table (5.1): Forward network parameters

Reservoir properties	
1	Permeability
2	Porosity
3	Rock compressibility
4	Reservoir depth
5	Reservoir thickness
6	Initial pressure
7	Temperature
8	Gas gravity
Well configuration	
9	Pattern size
10	Vertical distance for first branch
11	Horizontal length for first branch
12	Vertical distance for second branch
13	Horizontal length for second branch
14	Phase angle

Dual horizontal wells have five important parameters as shown in the previous table. Vertical length is the distance between the top of the reservoir and the depth at which horizontal drilling starts. Horizontal distance is the distance of the horizontal branch. Phase angle is the angle between the two horizontal branches. Figure (5.1) shows different parameters associated with a dual horizontal well completion.

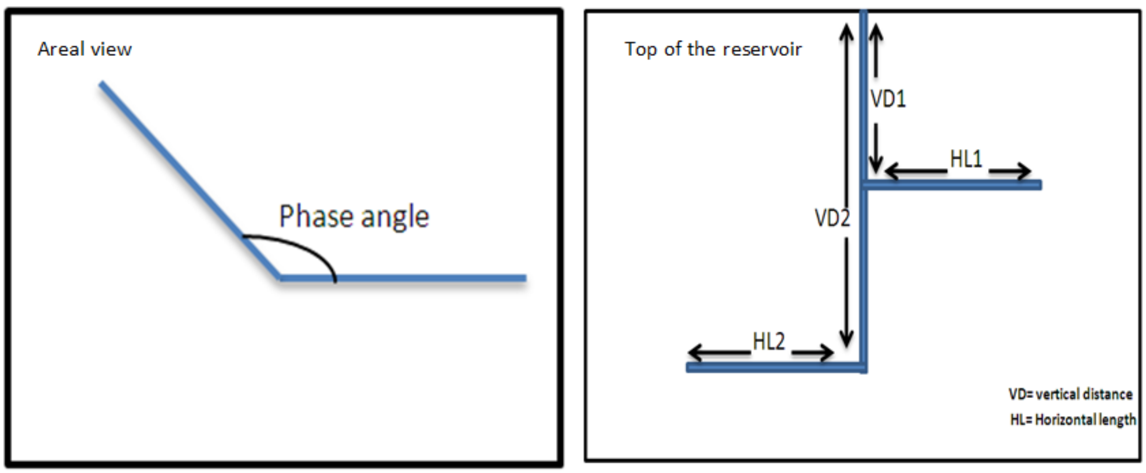


Figure (5.1): (a) Reservoir areal view (b) Reservoir sectional view

The output of the forward network is the gas recovery profile for a time period of 50 years, which displays the cumulative gas recovery of the well over the time, which guides the user in making many decisions about the reservoir.

5.1 TRAINING PROCESS

The first step of the training process is dividing the generated data into three sets; a training set, a validation set and a testing set. The generated data base contains of 1250 cases divided based on 80/10/10 rule to 1000, 125, 125 cases. In order to achieve the best performance of the network and minimize the difference between the simulator output and the network's output, many training processes have been conducted to choose the best architecture, number of hidden layers, number of neurons in each layer, transfer function, learning function and training function. Figure (5.2) shows the network which provided satisfactory results.

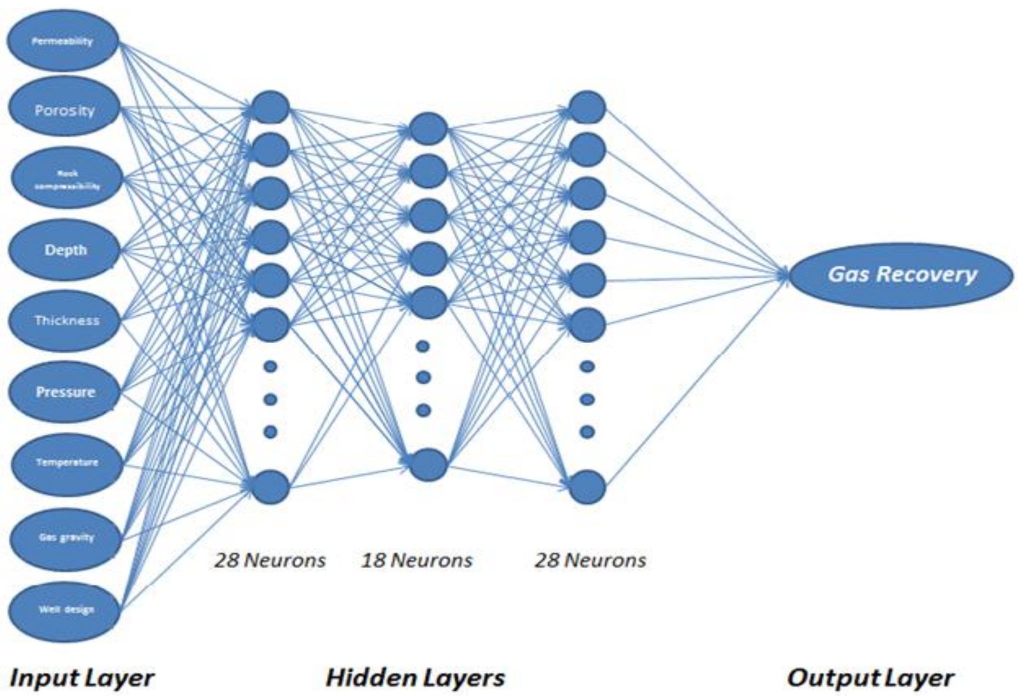


Figure (5.2): Forward network

Three hidden layer feed forward back-propagation provided satisfactory results for the input/output relationship function with a mean square error of 7.5%. The number of neurons at the three hidden layers are; 28, 18 and 28. *Tan sigmoid* is the transfer function utilized and conjugate gradient with Powell-Beale Restarts is the learning algorithm.

5.2 TESTING AND VALIDATION FORWARD NETWORK

Three methods have been used to test and validate the accuracy of the network. The mean square error, plotting the simulator output and the network generated output and testing a new set of data are the three methods as explained below.

a. Mean Square Error

Mean square error has been calculated for each single training process. Mean square error of the simulator output and the network generated output have been calculated as the first step in selecting the best network that can introduce a function which explains the relationship between the input and the output. After training many networks, the mean square error decreased from 65% to 7.5%.

b. Plotting the Actual Output Versus the Network Generated Output

Random cases from the testing set have been picked in order to compare the simulator recovery versus the network generated recovery. As mentioned before, this study's goal is to guide the user by providing a reliable recovery profile, so that plotting the simulator recovery profile versus the network generated recovery profile is important in providing a comparative analysis. Figures (5.3), (5.4), (5.5), and (5.6) display a sample of the recovery plots. After comparing the recovery profiles, the selected network provided a satisfactory curve fitting. Then, generating a fresh set of data is very important to test the network. Appendix (A) contains the reservoir properties and the well configuration used in the sample tests.

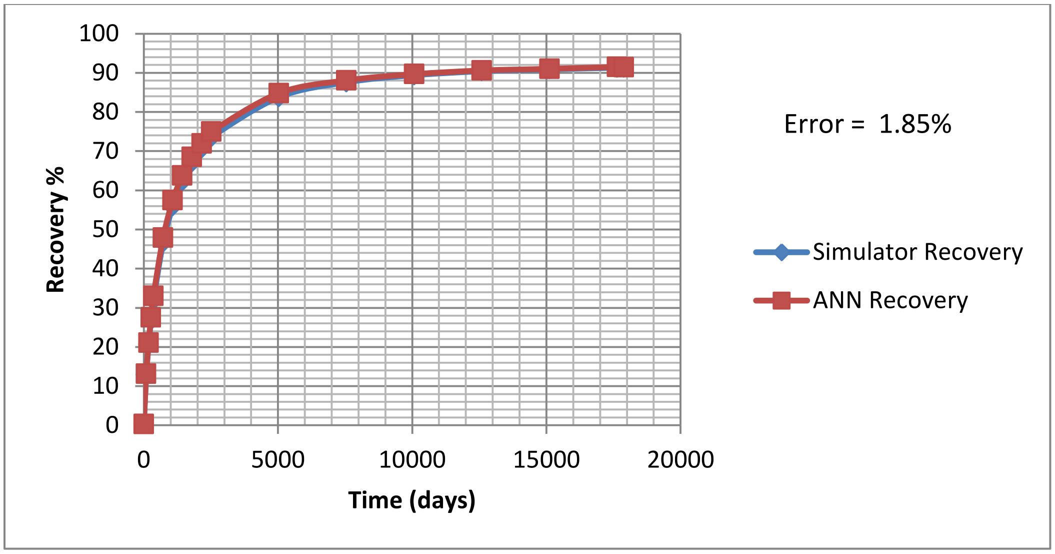


Figure (5.3): Sample test no.1

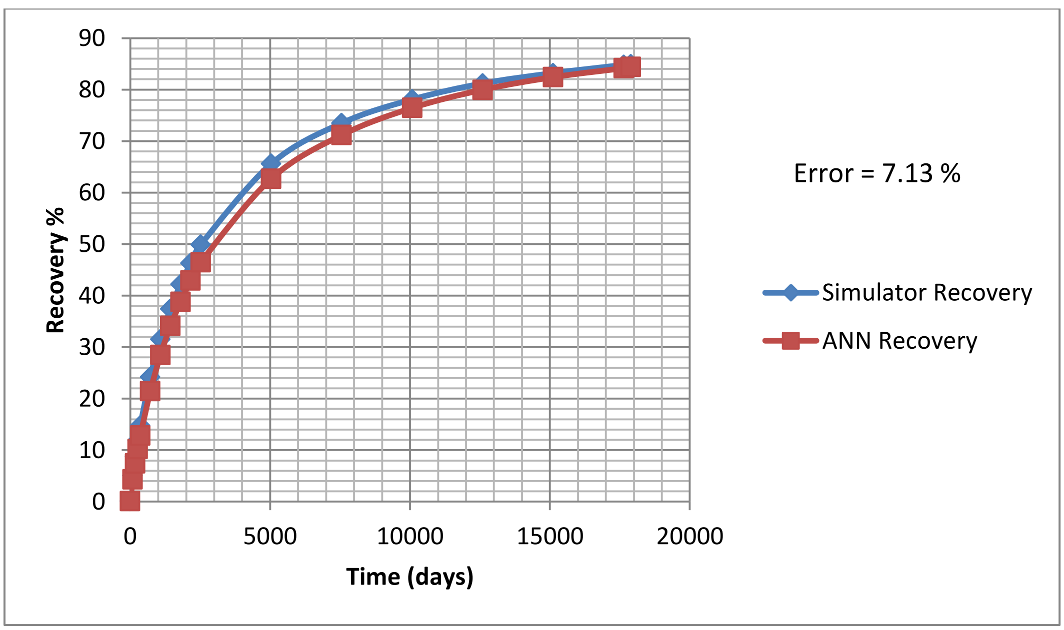


Figure (5.4): Sample test no.2

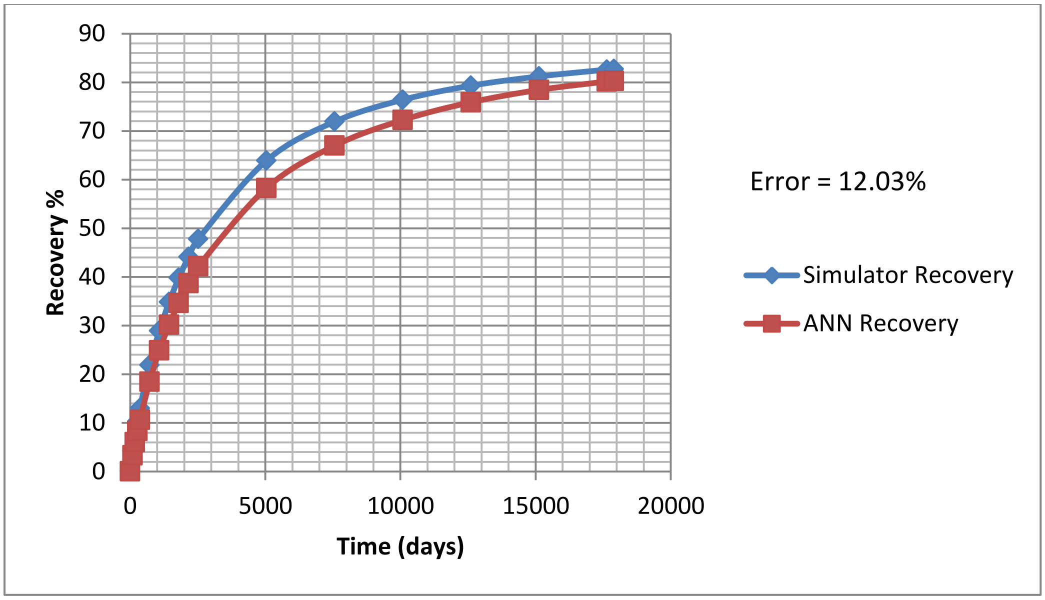


Figure (5.5): Sample test no.3

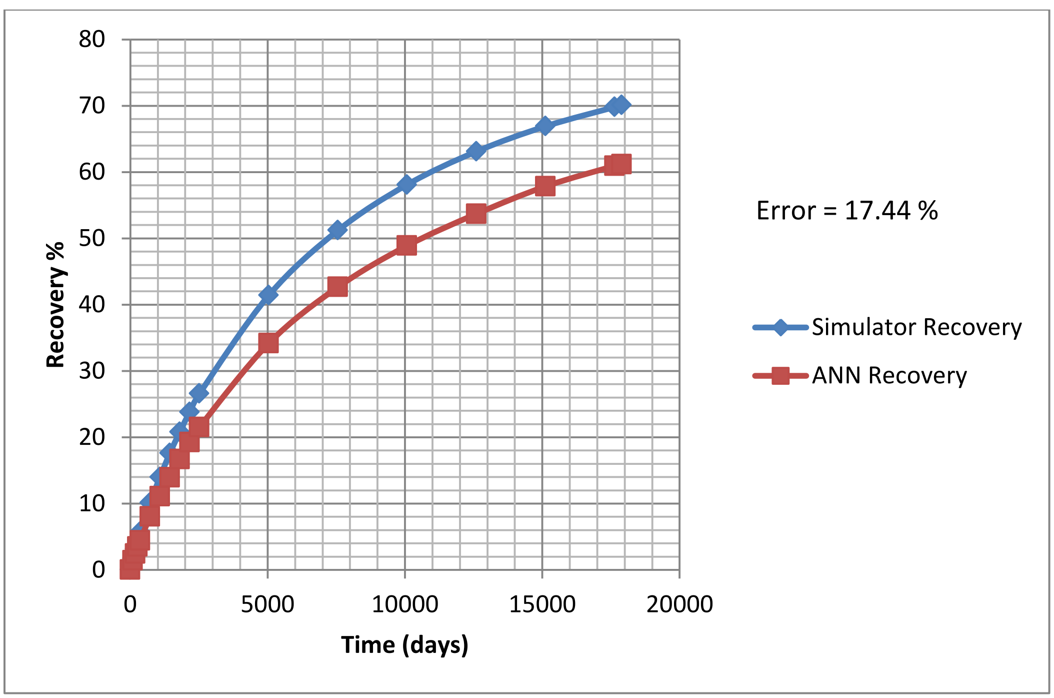


Figure (5.6): Sample test no.4

c. Testing with Fresh Data

Fresh data have been generated in order to test the network. Three sets have been generated including 50, 250 and 500 cases. The properties of each set have been used as an input for the network to be trained in order to predict the cumulative recovery profile for 50 years. After the training process, the mean square error was calculated and plot of the simulator recovery and the network generated recovery profile is generated. Analysis of the mean square errors help in showing the variety range of errors encountered.

i. The First Set (50-case study)

The calculated mean square error of the first 50-case study, between the simulator recovery and the network generated recovery, is 6.09%. Figure (5.7) shows the variation of error margins with the number of the cases investigated. Figures (5.8), (5.9), (5.10), (5.11) show randomly picked plots of the simulator recovery and network generated recovery curves.

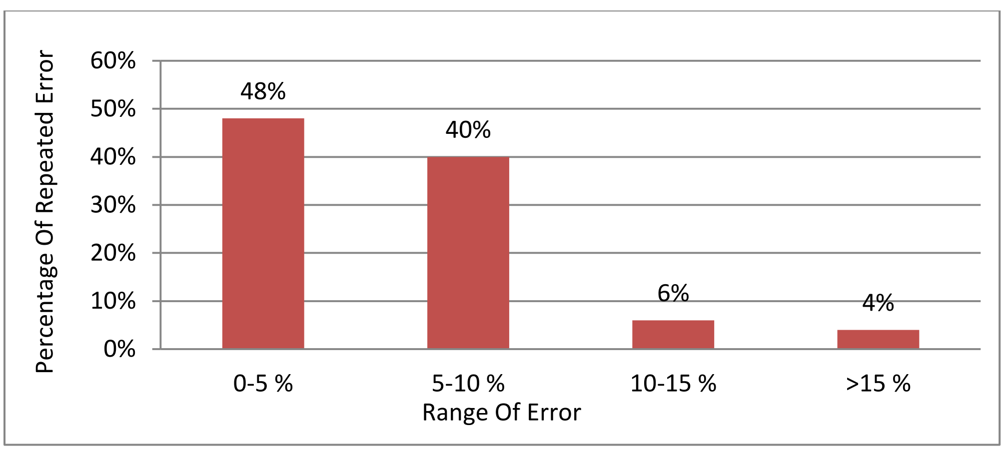


Figure (5.7): The variation range of errors in 50 cases

The cases which showing an error between 10-15% are:

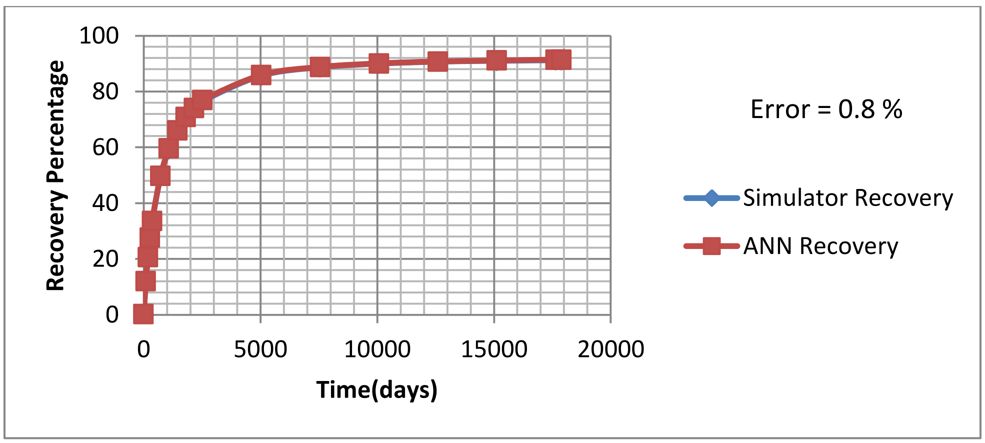
- Low permeability (0.0001-0.001md).

- Tight reservoirs (thickness 50-100 ft.).
- Small pattern size (27- 50 acres)

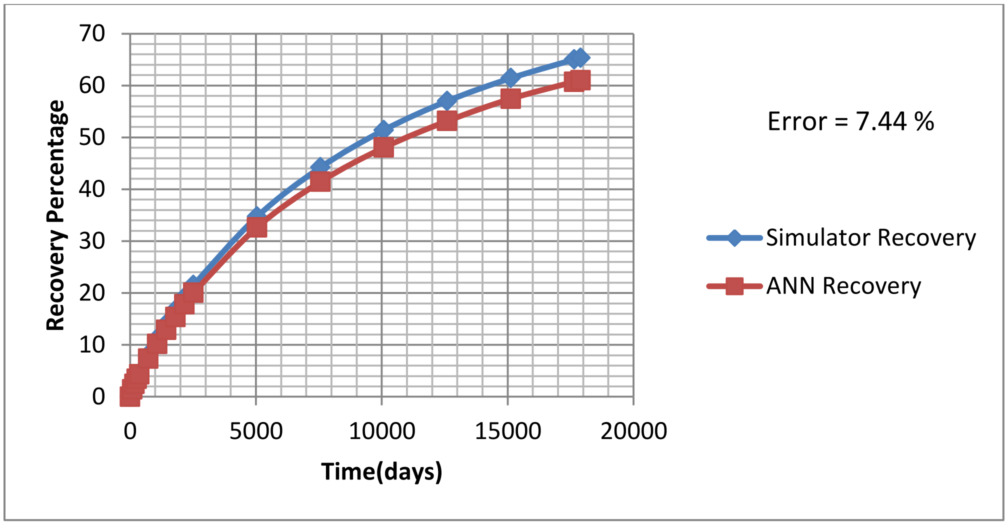
The cases which showing an error higher than 15% have:

- Low vertical permeability(0.0001-0.001md)
- High horizontal permeability (0.1-1 md).
- Short horizontal well lengths

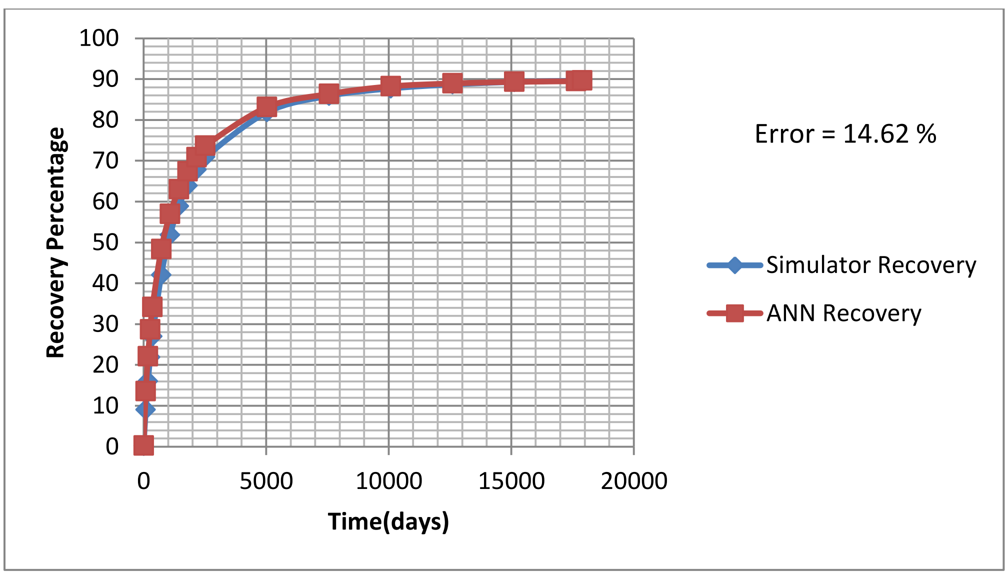
Appendix (B) contains the reservoir properties and the well configuration for the 50 cases tested.



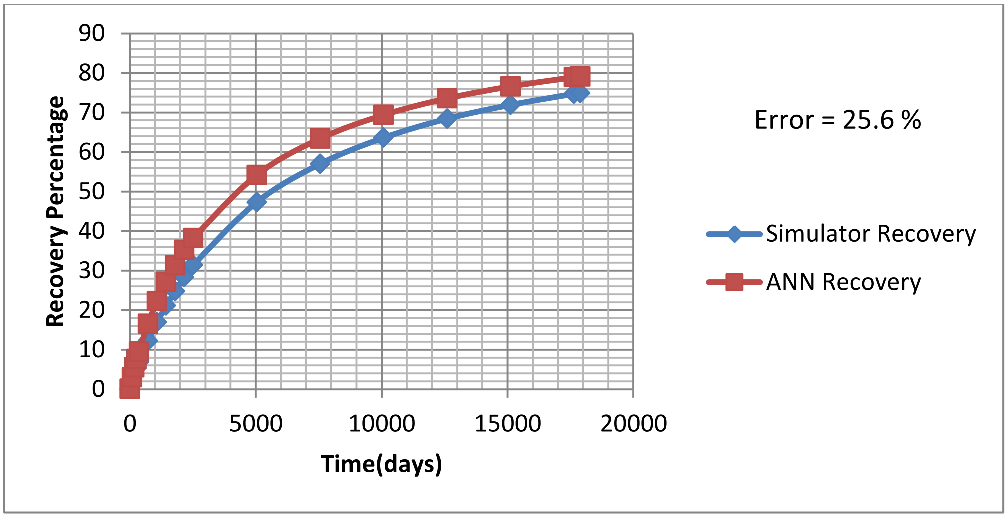
Figures (5.8): Sample result from 50-case study with error < 5%



Figures (5.9): Sample result from 50-case study with 5% <error < 10%



Figures (5.10): Sample result from 50-case study with 10% <error < 15%



Figures (5.11): Sample result from 50-case study with error > 15%

ii. The Second Set (250-case study)

The calculated mean square error of the 250-case study, between the simulator recovery and the network generated recovery, is 6.09%. Figure (5.12) shows the variation of error margins with the number of the cases investigated. Figures (5.13), (5.14), (5.15), (5.16) show randomly picked plots of the actual recovery and network's recovery curves.

Figure (5.12): The variation range of errors in 250 cases

The cases which showing an error between 10-15% are:

1. Tight reservoirs with a small distance between the horizontal branches and long horizontal lengths.
2. Thick reservoirs with a small distance between the horizontal branches and short horizontal lengths.

The cases which showing an error higher than 15% are:

1. Low permeability reservoirs (0.0001-0.001 md) with short horizontal lengths.
2. Thick reservoirs with a short distance between the horizontal branches and long horizontal lengths.

Appendix (C) contains the reservoir properties and the well configuration for the 250 cases tested.

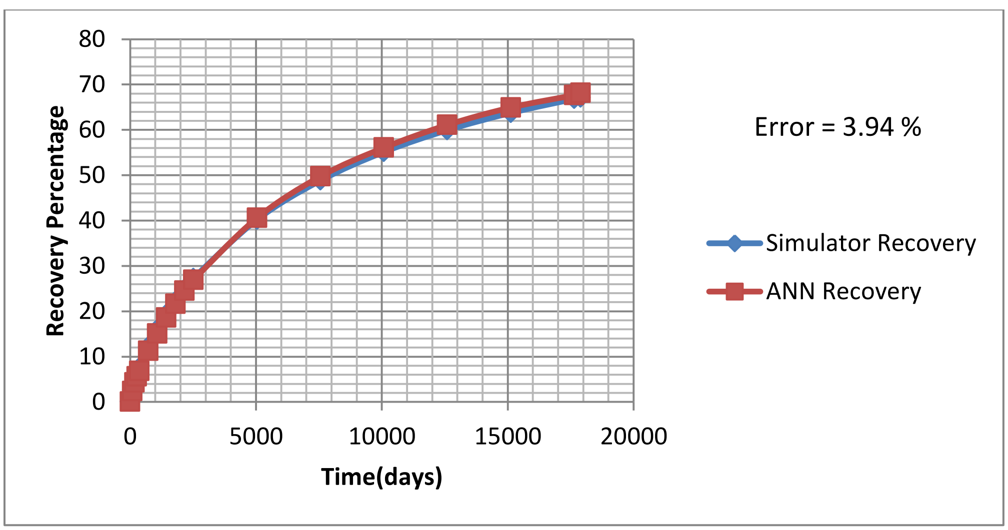


Figure (5.13): Sample result from 250-case study with error < 5%

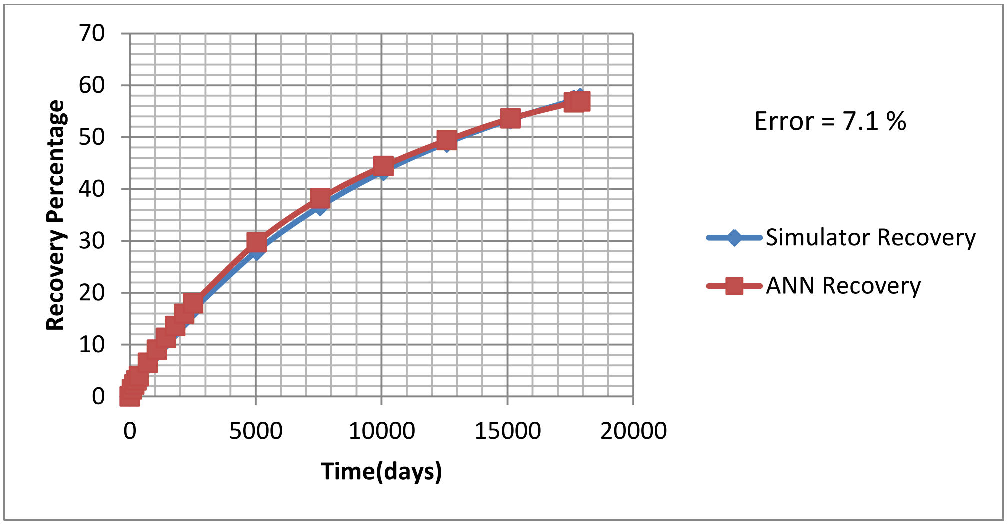


Figure (5.14): Sample result from 250-case study with 5% <error < 10%

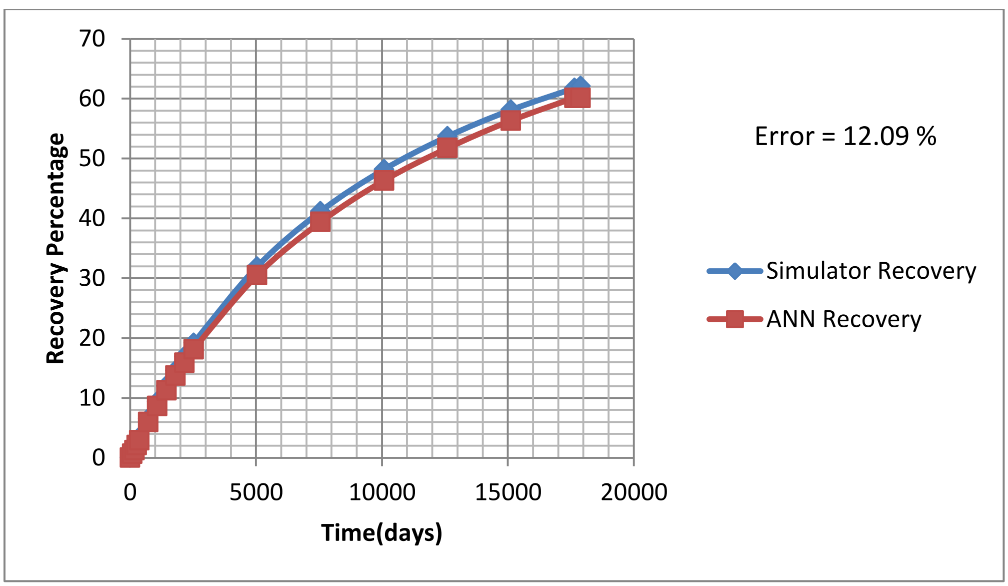


Figure (5.15): Sample result from 250-case study with 10% <error < 15%

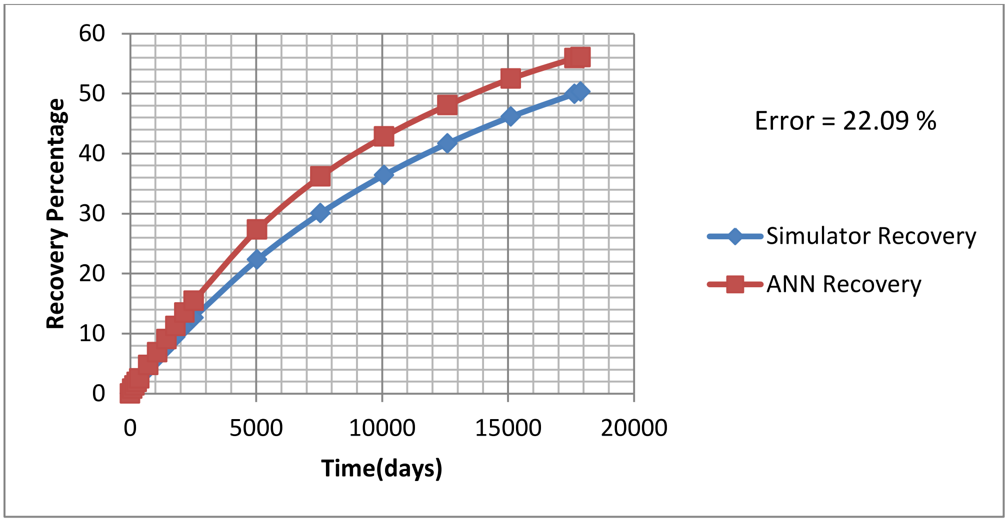


Figure (5.16): Sample result from 250-case study with error > 15%

iii. The Third Set (500-case study)

The calculated mean square error of the 500-case study, between the simulator recovery and the network generated recovery, is 8.83%. Figure (5.17) shows the variation of error margins with the number of the cases investigated. Figures (5.18), (5.19), (5.20), (5.21) show randomly picked plots of the actual recovery and network's recovery curves.

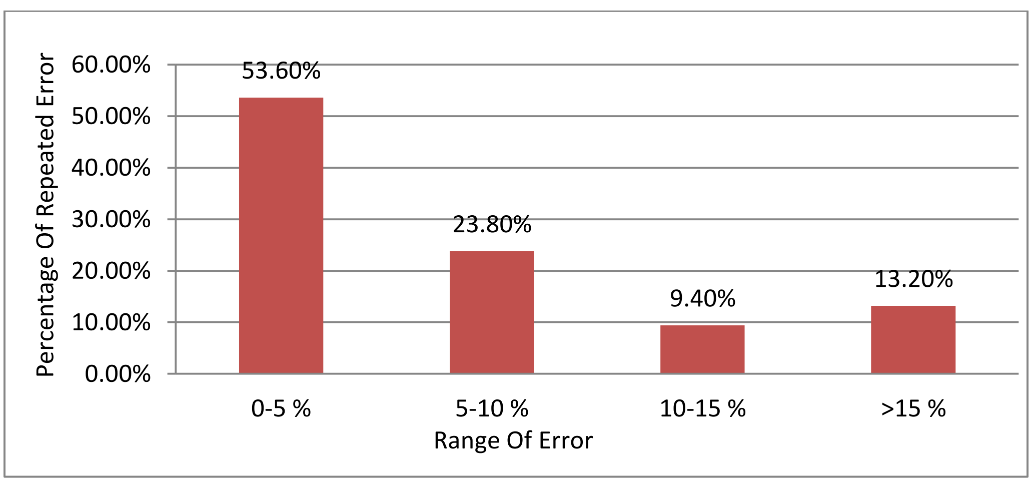


Figure (5.17): The variation range of errors in 500 cases

The cases which provided an error between 10-15% are:

1. Tight reservoirs with a small distance between the horizontal branches and long horizontal lengths.
2. Thick reservoirs with a small distance between the horizontal branches and short horizontal lengths.

The cases which provided an error higher than 15% are:

1. Low permeability reservoirs (0.0001-0.001 md) with short horizontal lengths.
2. Thick reservoirs with a short distance between the horizontal branches and long horizontal lengths.

Appendix (D) contains the reservoir properties and the well configuration for the 500 cases tested samples.

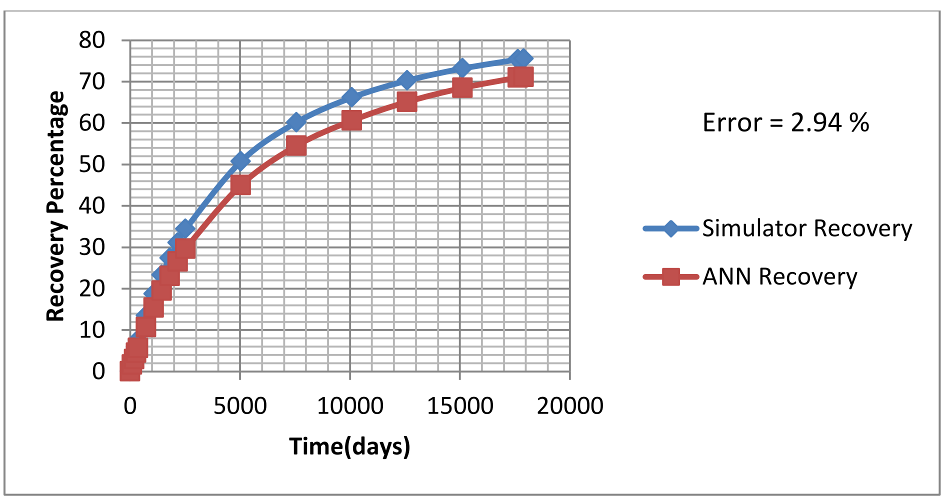


Figure (5.18): Sample result from 500-case study with error < 5%

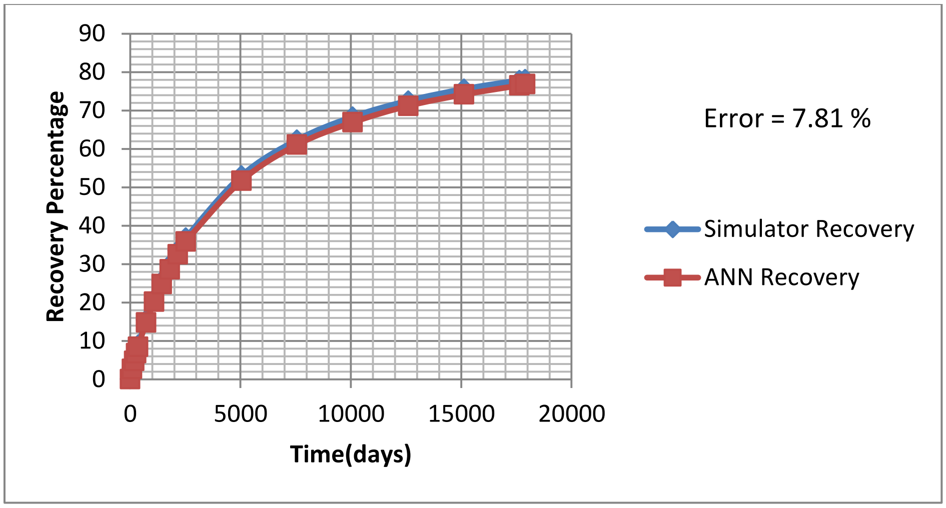


Figure (5.19): Sample result from 500-case study with 5% <error < 10%

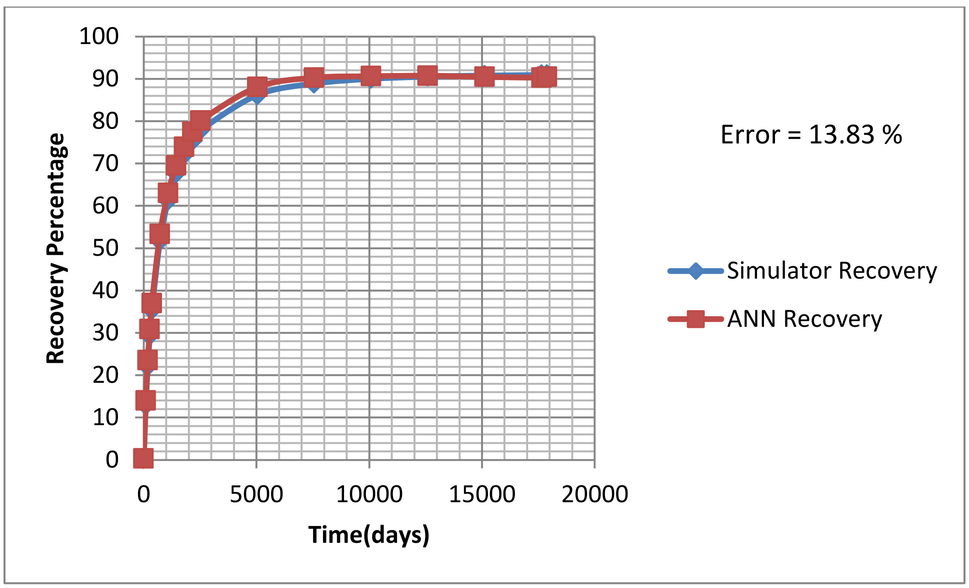


Figure (5.20): Sample result from 500-case study with 10% <error < 15%

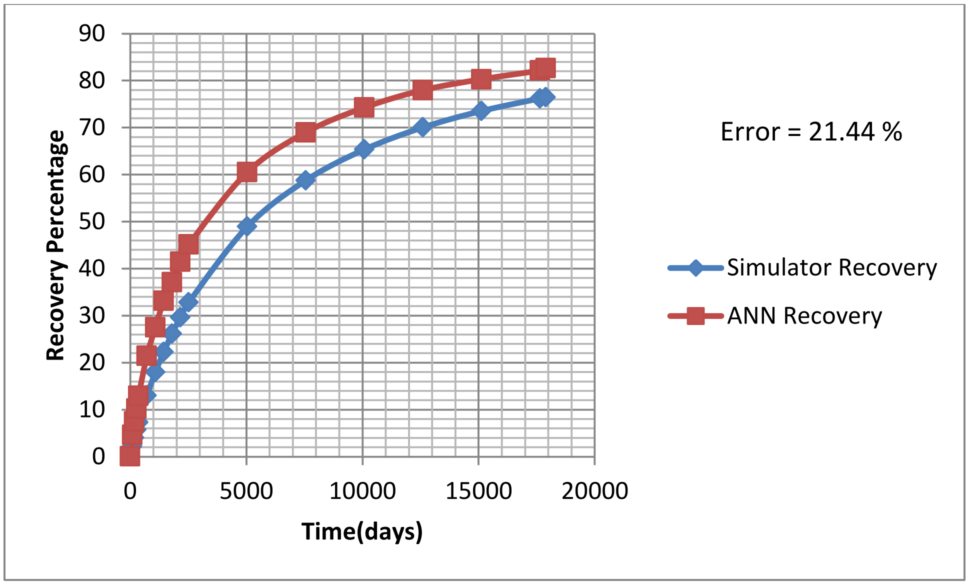


Figure (5.21): Sample result from 500-case study with error > 15%

5.3 MONTE CARLO SIMULATION

Monte Carlo simulation is generating a probabilistic analysis on different variables in the system by generating a random combination of the independent variables within certain pre-established limits and comparing the distribution of the results. In this study Monte Carlo simulation is used to generate the probabilistic analysis for the gas recovery after 50 years of production, for a number of random well configuration combinations, using the generated forward network. In order to generate the Monte Carlo analysis, the reservoir properties and the number of the random combination have to be identified. The simulation will generate random combinations of the well configuration parameters within the selected limits. Then, the forward network is going to generate the recovery profile and extract the final cumulative recovery after 50 years. Finally, a probabilistic distribution will be generated which shows the distribution of the cumulative recovery.

5.3.1 Example

The following table contains the reservoir and rock properties within the forward network limits.

Table (5.2): Reservoir properties

Reservoir properties		
1	Permeability vertical	.08149 md
2	Permeability horizontal	.582667 md
2	Porosity	.18
3	Rock compressibility	.0000000861
4	Reservoir depth	7134 ft.
5	Reservoir thickness	385 ft.
6	Initial pressure	7037 psi
7	Temperature	240 F
8	Gas gravity	.54

In this example, 10,000 random combinations of the well configuration parameters have been generated to be trained by the forward network. Probabilistic analysis for the well recovery is generated as shown in the following figure.

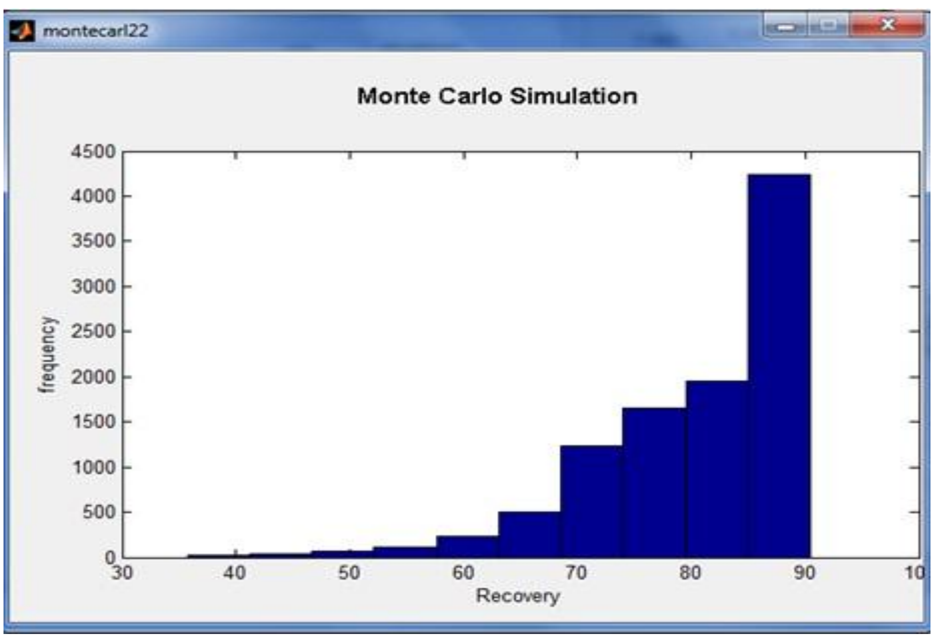


Figure (5.22): Monte Carlo simulation for 10,000 cases

The analysis show that 4300 random well configuration's parameters combinations recover 85-90% of the reservoir gas in place after 50 years of production. This analysis implies that almost 50 % of the dual horizontal wells recover 85-90% of the gas in place for the selected reservoir and rock properties.

The benefit of using the Monte Carlo simulation with the ANN network is generating a large number of probabilities in less than 30 seconds and gives an estimation of the cumulative recovery after the 50 years of production.

Chapter 6

INVERSE NETWORK DEVELOPMENT

The inverse network has been generated to design a dual horizontal well configuration for a known reservoir properties and a desired cumulative gas recovery profile. The well produces at 500 psi bottom hole pressure. The reservoir properties and the desired cumulative gas recovery over 50 years are the inputs for the inverse network. Table (6.1) shows the input parameters used in generating the network.

Table (6.1): Inverse network parameters

(A)	**Reservoir Properties**
1	Permeability
2	Porosity
3	Rock compressibility
4	Reservoir depth
5	Reservoir thickness
6	Initial pressure
7	Temperature
8	Gas gravity
(B)	**Cumulative gas recovery over 50 years**

The output of the inverse network is the dual horizontal well configuration's parameters as shown in Table (6.2) and shown in Figure (6.1).

Table (6.2): Well configuration parameters

Well configuration	
1	Pattern Size
2	Vertical distance for first branch
3	Horizontal length for first branch
4	Vertical distance for second branch
5	Horizontal length for second branch
6	Phase angle

6.1 TRAINING PROCESS

The first step of the training process is dividing the generated data into three sets; training set, validation set and testing set. The generated data base consists of 1250 cases divided based on 80/10/10 rule to 1000, 125, 125 cases. In order to achieve the best performance and minimize the difference between the simulator output and the network generated output, many training processes have been studied to choose the best architecture, number of hidden layers, number of neurons in each layer, transfer function, learning function and training function. Figure (6.1) shows the network which provided satisfactory results.

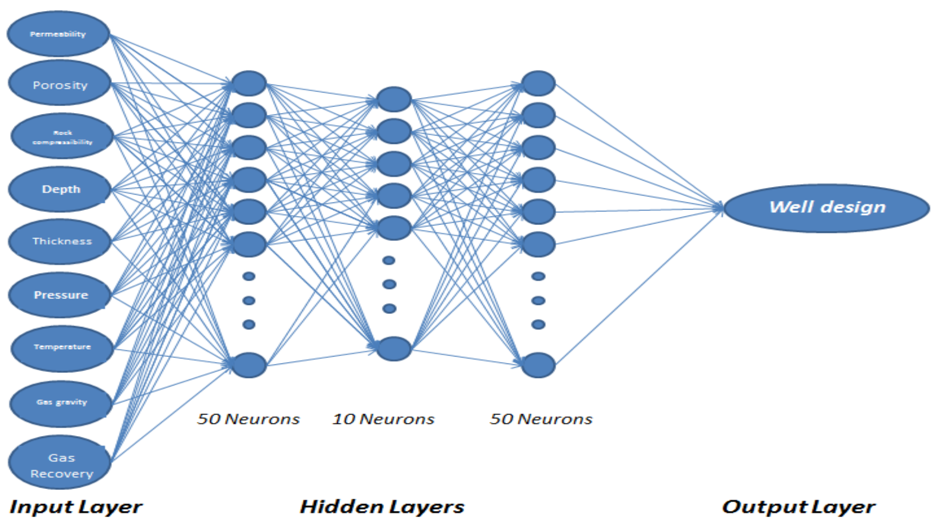


Figure (6.1): Inverse network

A three hidden layer feed forward back-propagation structure provided satisfactory results for the input output function with a mean square error of 40.01%. The number of the neurons at the three hidden layers were; 50, 10, and 50. The *Tan sigmoid* is the used as the transfer function and conjugate gradient with *Powell-Beale Restarts* as the learning algorithm.

While the error between the actual output and the network's output is 40.01%, the error amount between the desired recovery and the recovery of the predicted well configuration is only 9.8%. The desired recovery and the predicted well configuration's recovery have been compared in the testing, as the main goal of the inverse is achieving the desired recovery profile.

6.2 TESTING AND VALIDATION INVERSE NETWORK

Three methods have been used to test the network. Mean square error, recovery profiles comparing and testing a new set of data is the three methods as explained below.

a. Mean Square Error

Mean square error has been calculated for each single training process. Mean square error of the actual output and the network's output have been calculated as the first step in selecting the best network can introduce function explains the relationship between the input and the output. After training many networks, the mean square error decreased from 95% to 40.01%.

b. Comparison of the Recovery Profiles

In order to verify that the desired recovery will be the same as the recovery of the predicted well configuration, Recovery profile for the predicted well configuration has been generated by the simulator. The mean square error between the desired recovery and the simulator recovery for the ANN well configuration is 9.56%.

c. Testing with Fresh Data

A new set of fresh data has been generated for testing the selected network. Three sets have been generated include 50, 250 and 500 cases. The properties of each set have been used as an input for the network to be trained in order to predict the well configuration for the desired recovery. After the training process, recovery profile is generated by the reservoir simulator using the reservoir properties and the network predicted well configuration parameters. Analysis of the mean square errors generated to show the variation of the range of errors and random selected cases to show the desired recovery profile versus the ANN well configuration profile.

i. The First Set (50-case study)

The calculated mean square error of the 50-case study, between actual and the ANN well configuration's recovery, is 10.25%. Figure (6.2) shows the variation of error margins with the number of the cases investigated. Figures (6.3), (6.4), (6.5), (6.6) show randomly picked plots of a desired recovery and a network well configuration recovery curves.

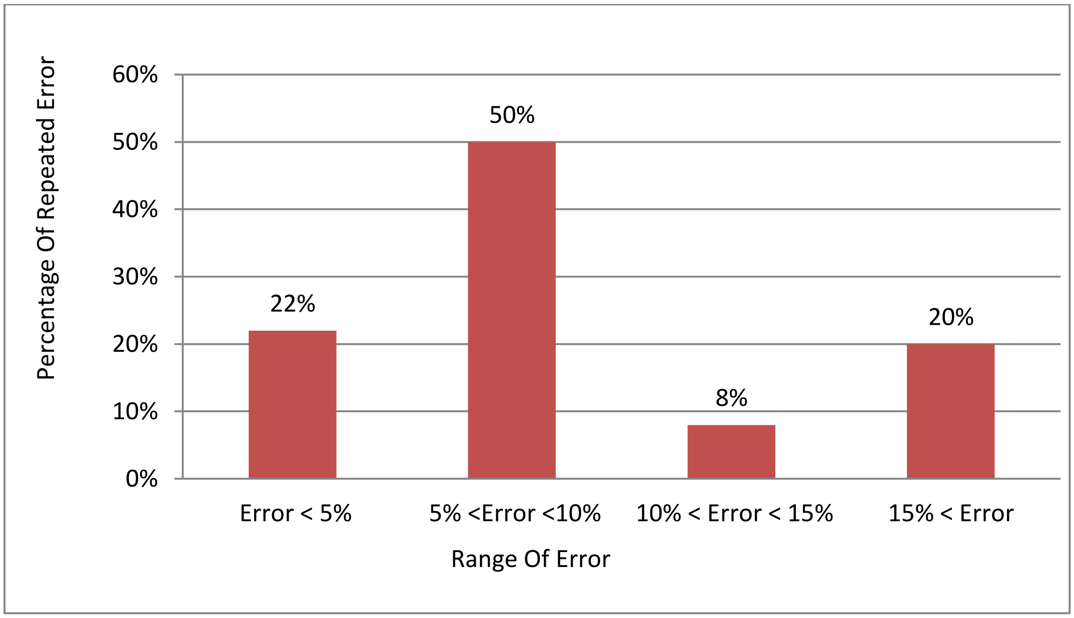


Figure (6.2): The variation range of errors in 50 cases (Inverse network)

The studied cases which provided a mean square error of more than 15% are low permeability reservoirs (0.0001-0.001 md) with high porosity fraction (0.17-0.25).

Appendix (E) contains the reservoir properties and the well configuration for the 50 cases tested.

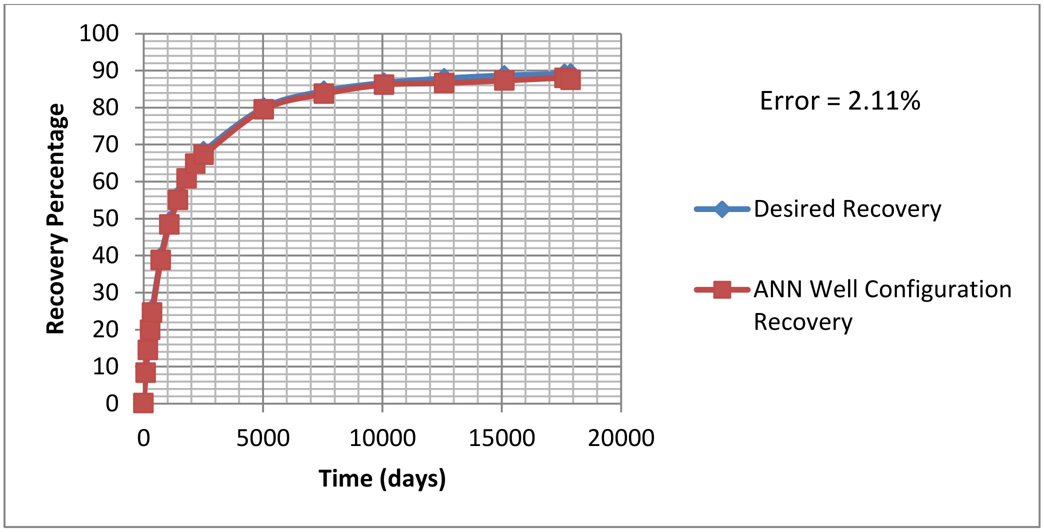


Figure (6.3): Sample result from 50-case study with error < 5% (Inverse network)

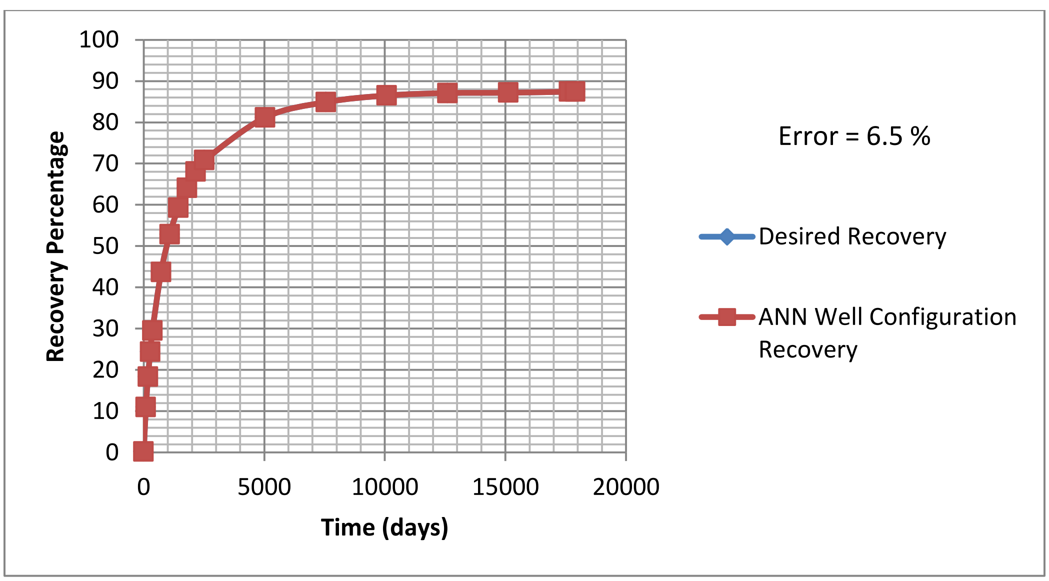


Figure (6.4): Sample result from 50-case study with 5% <error < 10% (Inverse network)

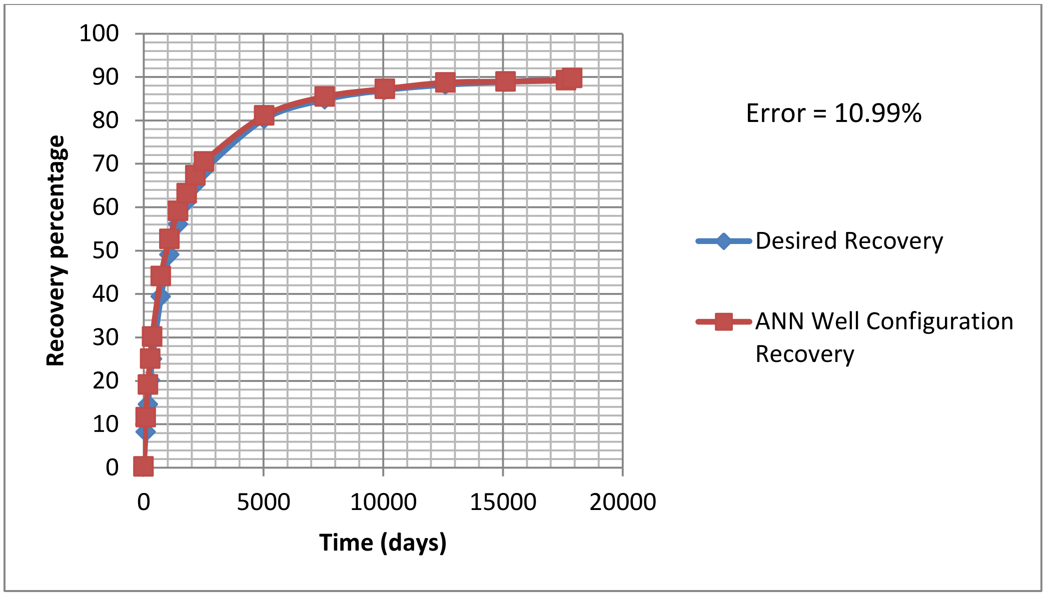


Figure (6.5): Sample result from 50-case study with 10% <error < 15% (Inverse network)

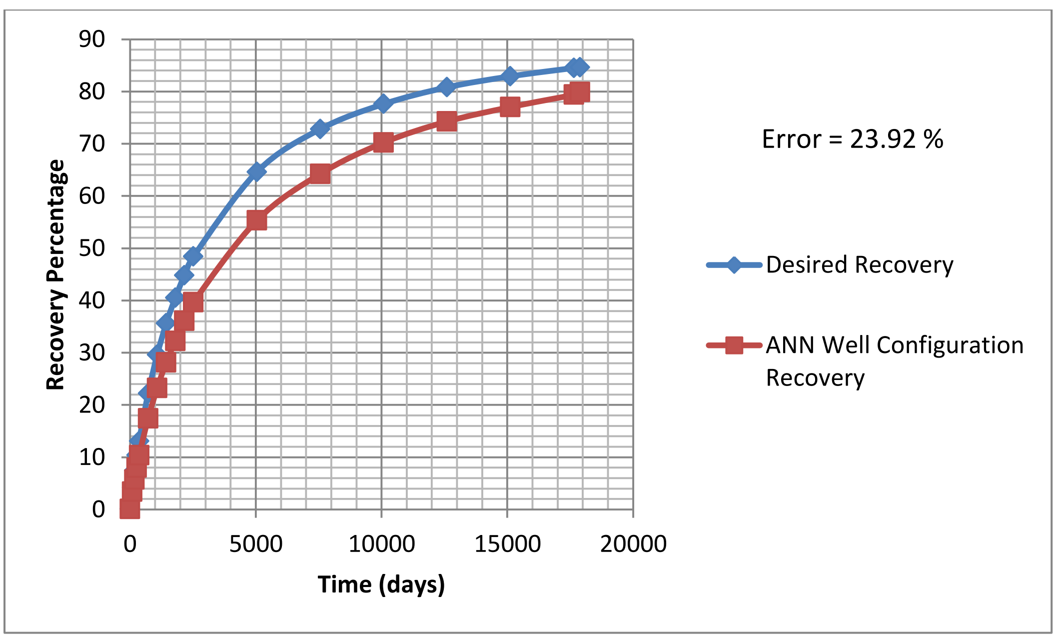


Figure (6.6): Sample result from 50-case study with error > 15% (Inverse network)

ii. The Second Set (250-case study)

The calculated mean square error of the 250-case study, between actual and the ANN well configuration's recovery, is 12.69%. Figure (6.7) shows the variation of error margins with the number of the cases investigated. Figures (6.8), (6.9), (6.10), (6.11) show randomly picked plots of the desired recovery and network well configuration recovery curves.

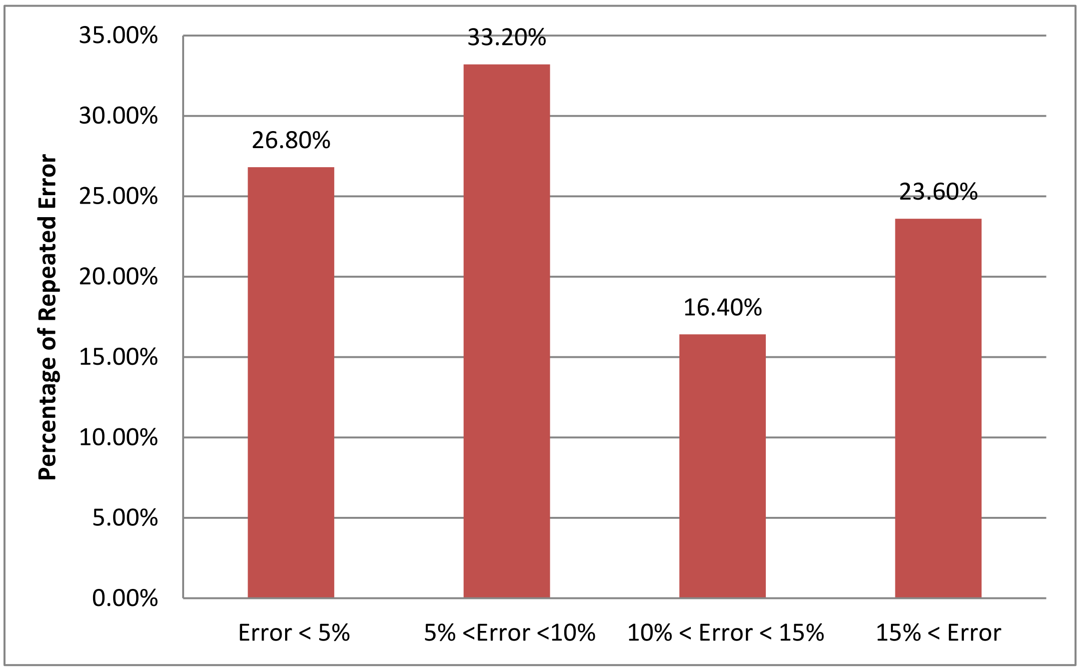


Figure (6.7): The variation range of errors in 250 cases (Inverse network)

The studied cases which provided mean square error more than 15% are low permeability reservoirs (0.0001-0.001 md) with high porosity fraction (0.17-0.25).

Appendix (F) contains the reservoir properties and the well configuration for the 250 cases tested.

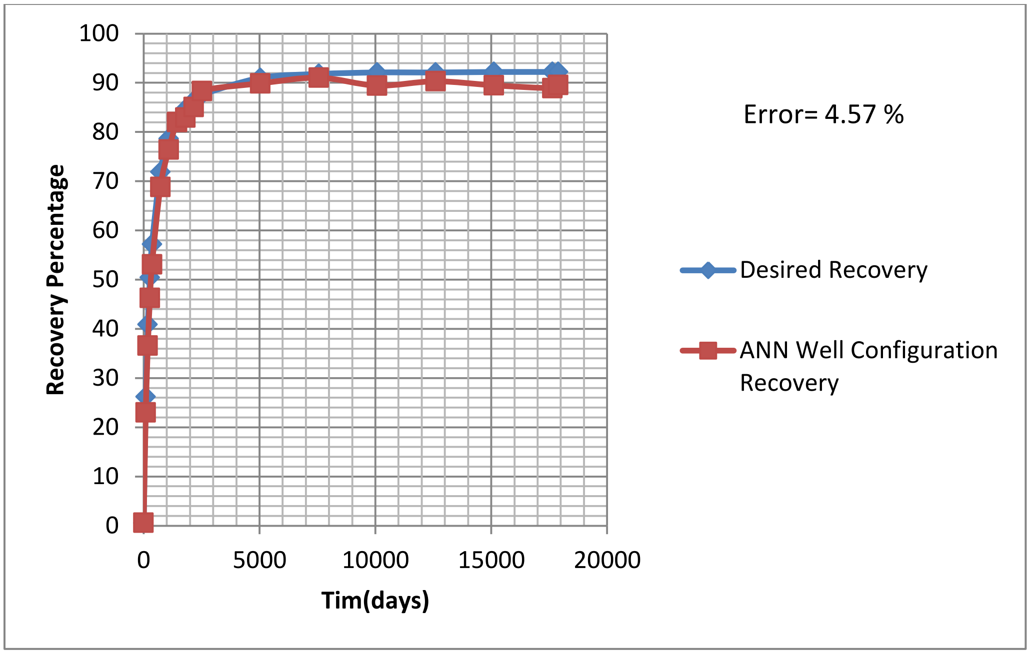


Figure (6.8): Sample result from 250-case study with error < 5% (Inverse network)

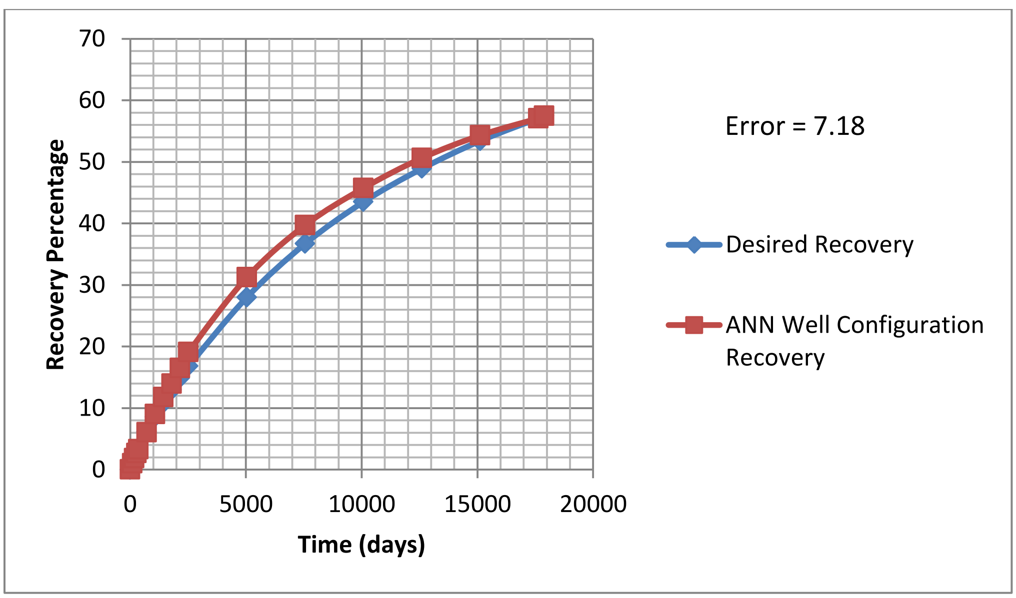


Figure (6.9): Sample result from 250-case study with 5% <error < 10% (Inverse network)

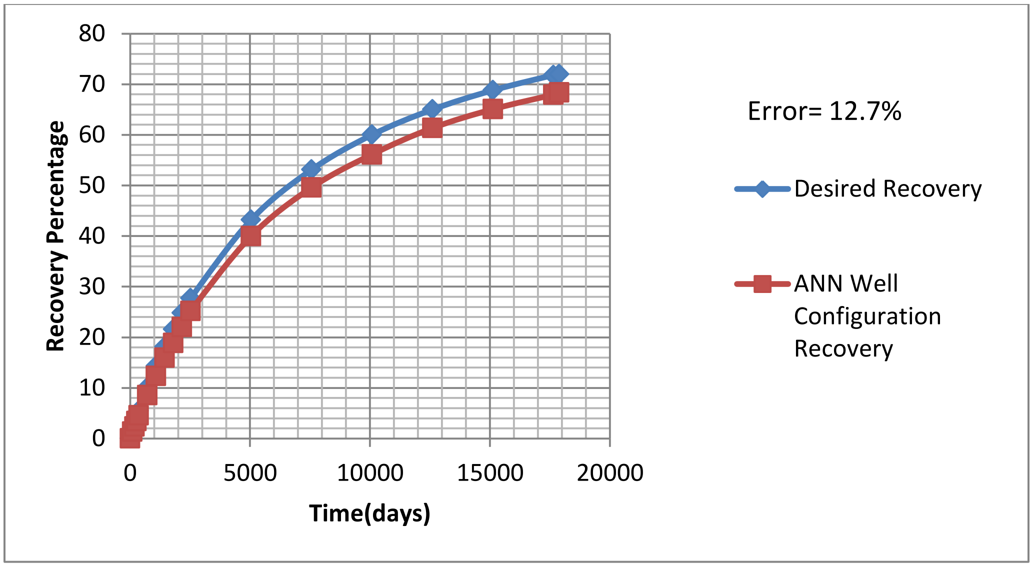


Figure (6.10): Sample result from 250-case study with 10% <error < 15% (Inverse network)

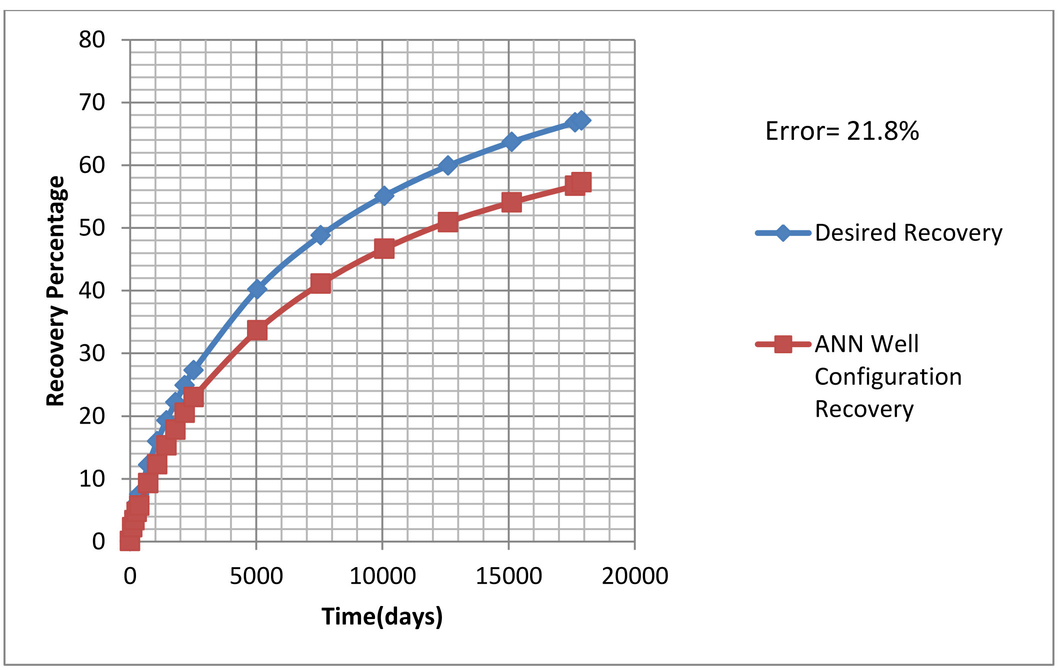


Figure (6.11): Sample result from 250-case study with error > 15% (Inverse network)

iii. The Third Set (500-case study)

The calculated mean square error of the 50-case study, between actual and the ANN well configuration's recovery, is 14.65%. Figure (6.12) shows the variation of error margins with the number of the cases investigated. Figures (6.13), (6.14), (6.15), (6.16) show randomly picked plots of the desired recovery and network well configuration recovery curves.

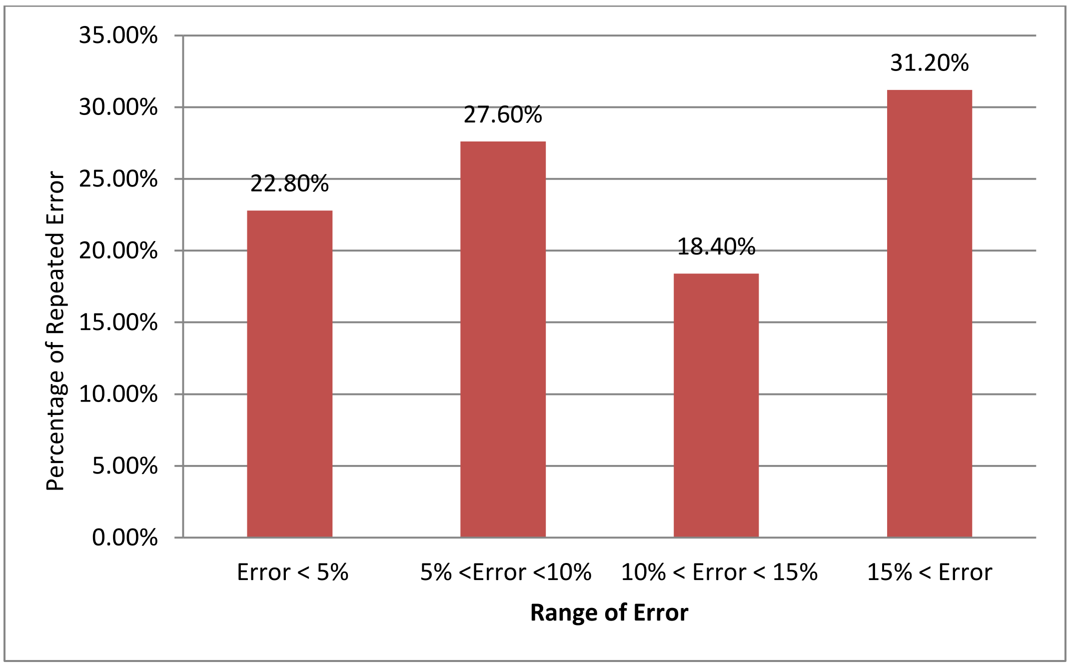


Figure (6.12): The variation range of errors in 500 cases (Inverse network)

The studied cases which provided mean square error more than 15% are low permeability reservoirs (0.0001-0.001 md) with high porosity fraction.

Appendix (G) contains the reservoir properties and the well configuration for the 500 cases tested.

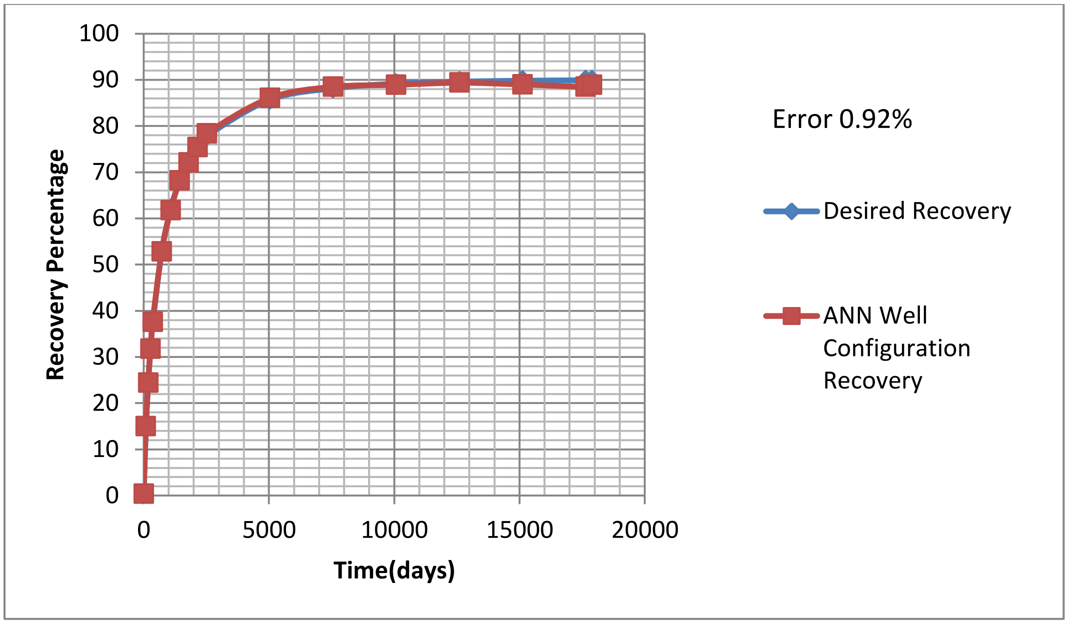


Figure (6.13): Sample result from 500-case study with error < 5% (Inverse network)

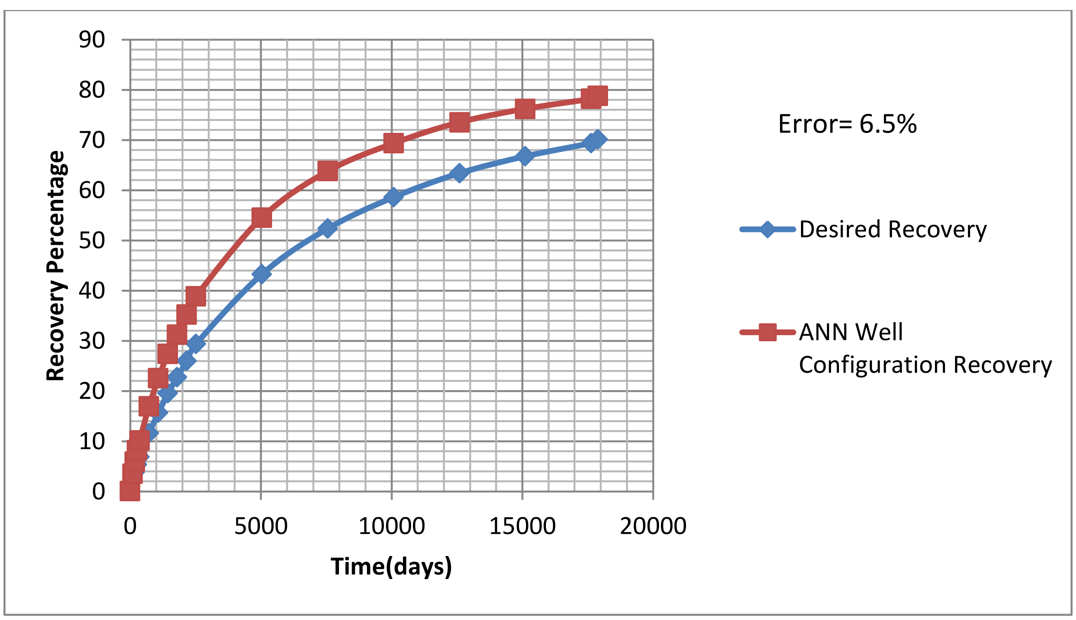


Figure (6.14): Sample result from 500-case study with 5% <error < 10% (Inverse network)

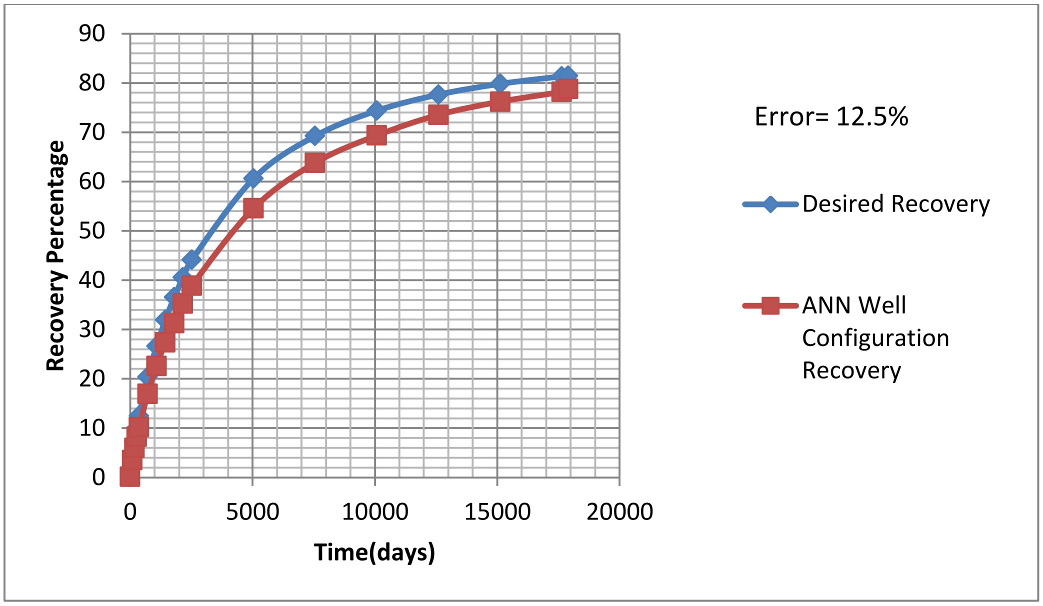


Figure (6.15): Sample result from 500-case study with 10% <error < 15% (Inverse network)

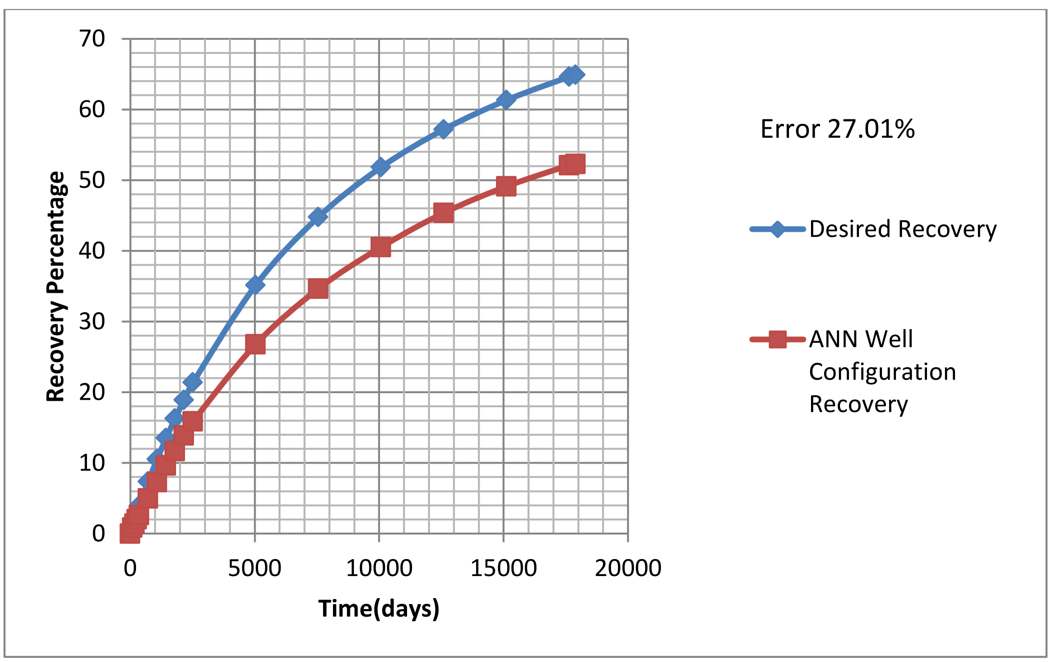


Figure (6.16): Sample result from 500-case study with error > 15% (Inverse network)

Chapter 7

GRAPHIC USER INTERFACE

The graphic user interface (GUI) is a MATLAB toolbox which helps the user in performing tasks interactively through controls such as buttons and sliders (Demuth, 2009). Graphic user interface have been created for the forward and the inverse networks to help the user in inserting the inputs and display the results. The enter screen of the GUI allows the user to choose forward or inverse to direct him to the right window as shown in the following figure.

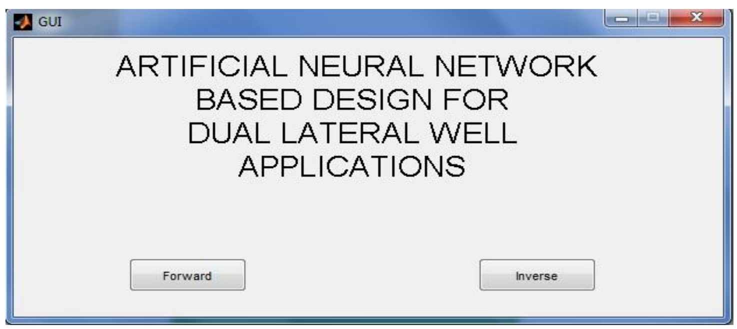


Figure (7.1): GUI enter screen

7.1 FORWARD GUI

The forward GUI allows the user to insert the reservoir properties and the well configuration parameters in order to predict the cumulative gas recovery for 50 years using the forward network. After inserting the required data, the network will predict the recovery profile by pressing the predict button. The forward GUI displays the cumulative gas production and the gas rate based on the recovery profile. The forward GUI allows the user to plot the recovery profile**,** the cumulative production and the gas rate separately and display their values as well. Figures (7.2) and (7.3) display randomly selected properties and its results using the forward GUI panel.

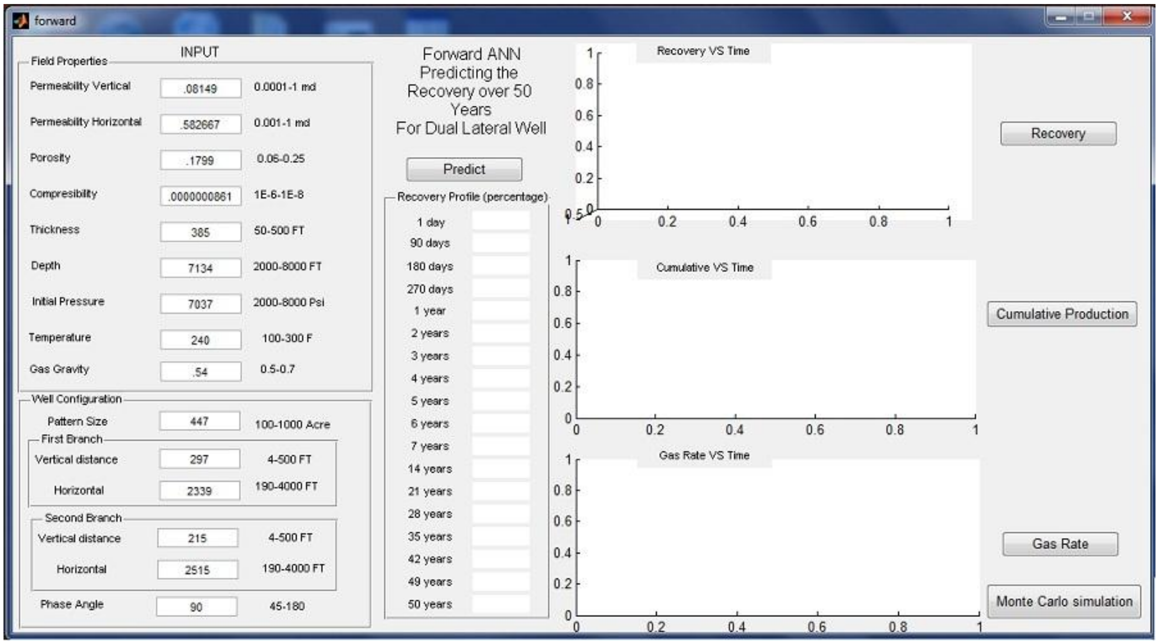


Figure (7.2): Forward GUI data entry panel

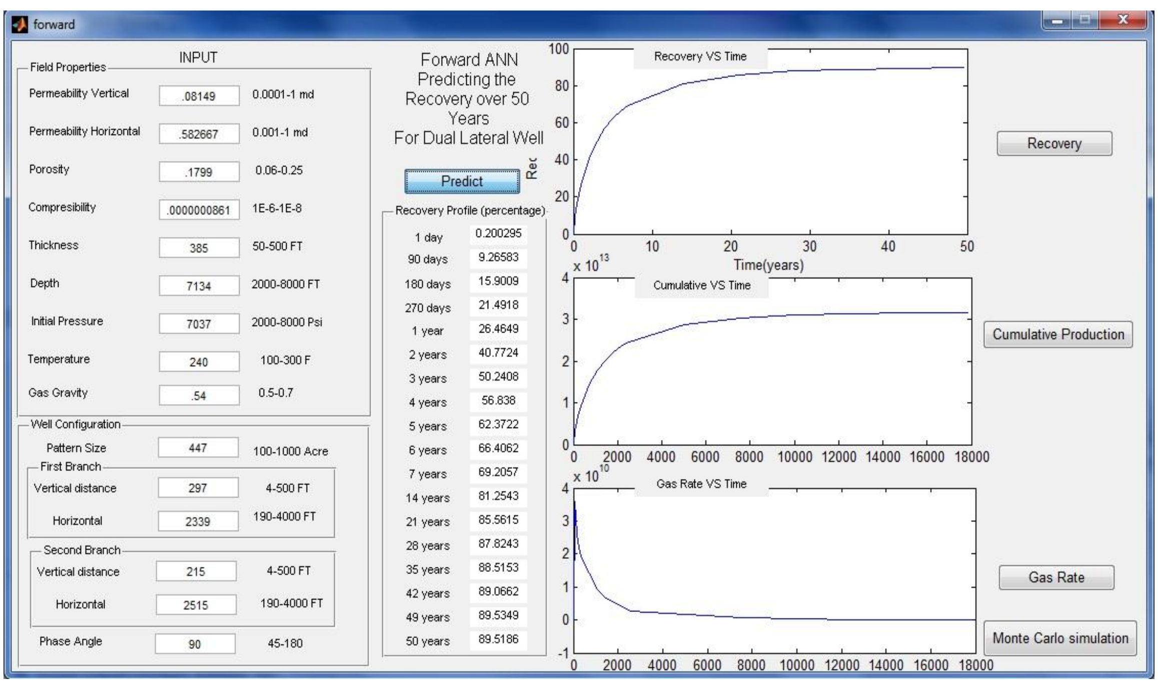


Figure (7.3): Forward GUI results panel

Monte Carlo simulation will be started by pressing the Monte Carlo button. Monte Carlo simulation calculates and compares the gas recovery at the end of the 50 years for different well configuration, as random combination of well configuration will be generated and the gas recovery will be calculated for each case. The user has to specify the number of the random combination desired to be compared.

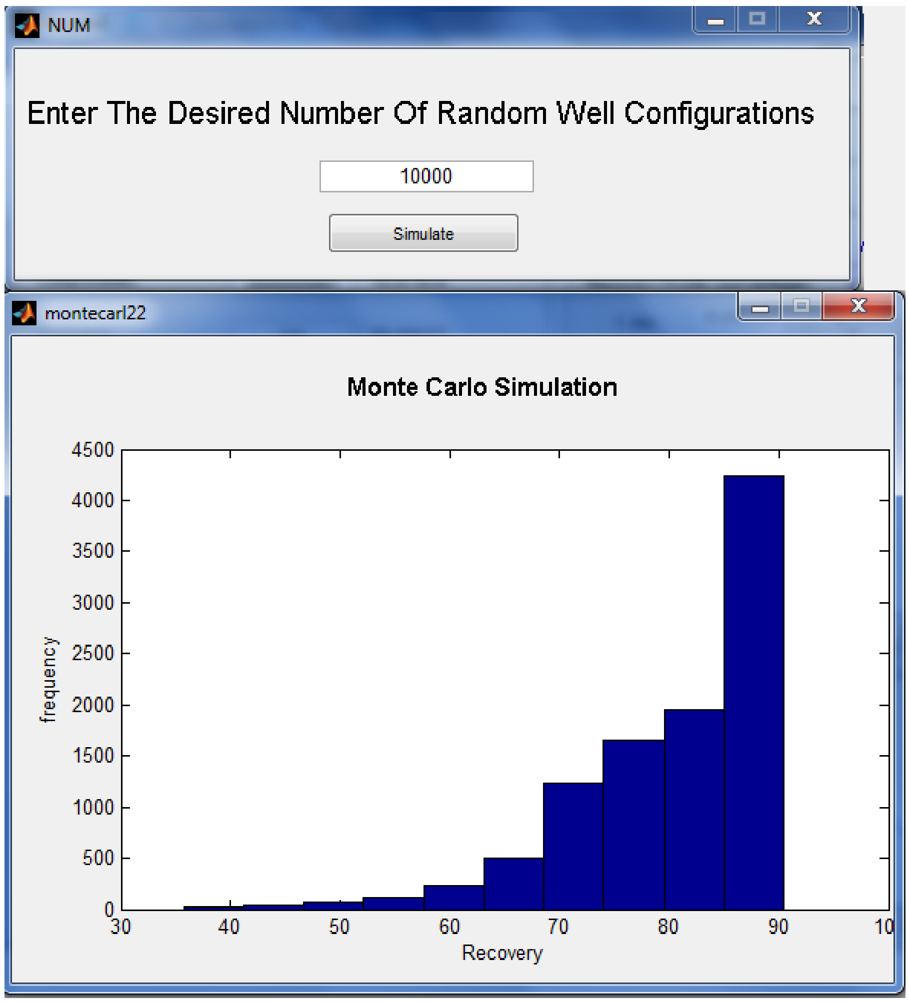


Figure (7.4): Monte Carlo simulation results for 10,000 cases

7.2 Inverse GUI

The inverse GUI allows the user to insert the reservoir properties and the desired gas recovery profile in order to predict the well configuration parameters using the inverse network. The inverse GUI gives the user an option to plot the desired recovery in order to verify the inserted data. After inserting the required data, the network will predict the well configuration parameters by pressing predict configuration button.

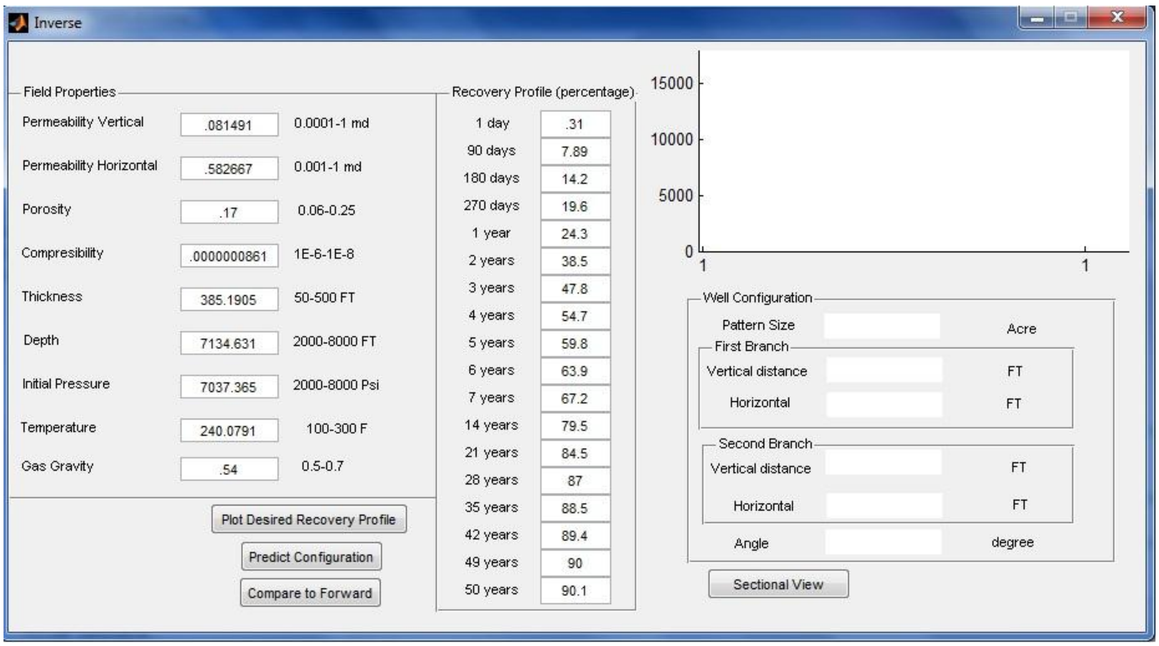


Figure (7.5): Inverse GUI data entry panel

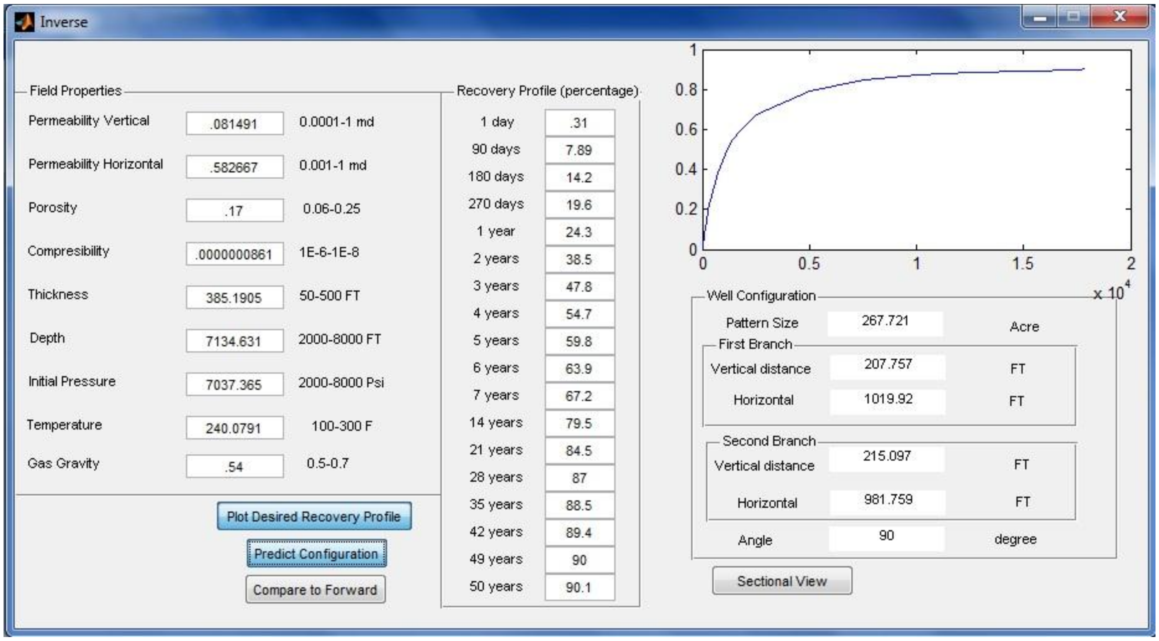


Figure (7.6): Inverse GUI results panel

The inverse GUI allows the user to display the sectional view for the predicted well configuration by pressing sectional view button in the inverse GUI data entry panel as shown below.

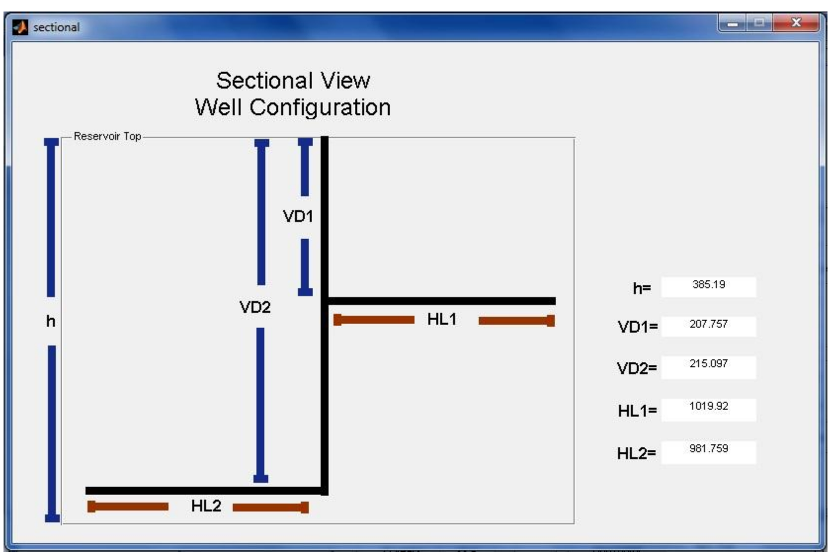


Figure (7.7): Sectional view

The inverse GUI also gives the user the opportunity to use the predicted well configuration with the inserted reservoir properties as an input for the forward network in order to predict the recovery profile for the well configuration which predicted by the inverse network and compare the desired recovery profile and the predicted well configuration recovery profile as shown in figure (7.8).

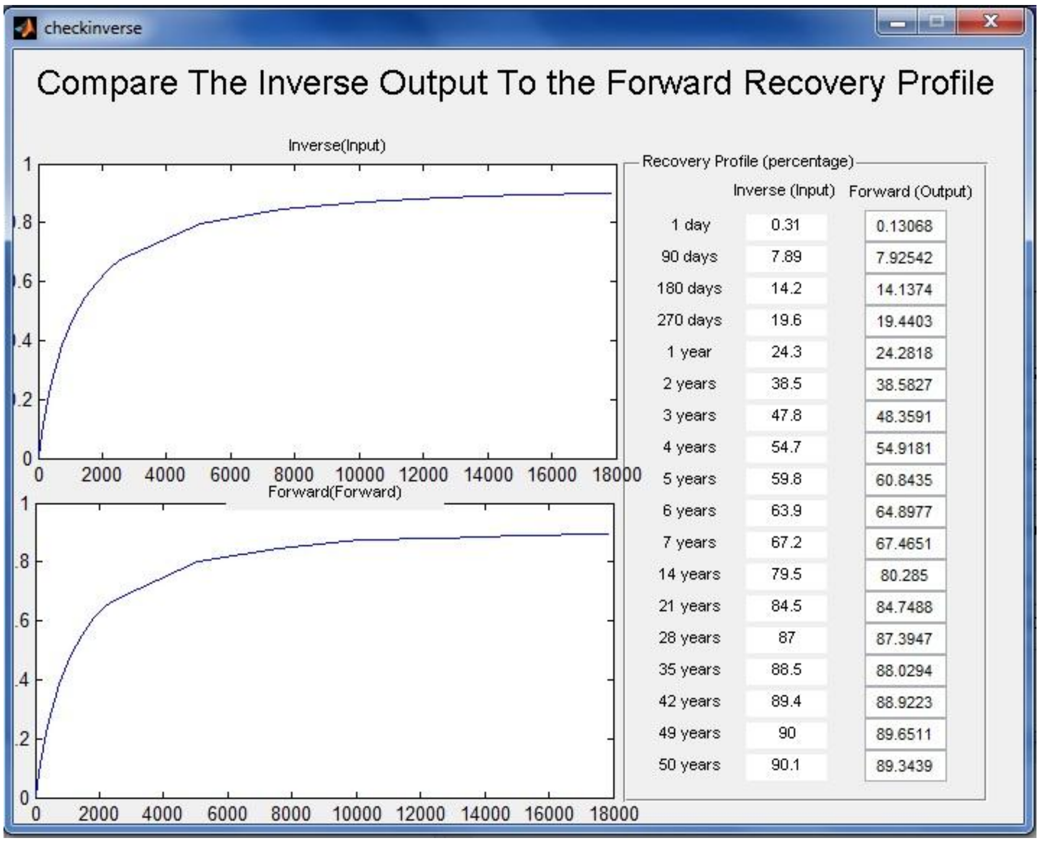


Figure (7.8): Comparing the inverse results to forward results

Chapter 8

SUMMARY OF RESULTS, CONCLUSION AND RECOMENDATIONS

8.1 RESULTS

The generated forward network developed on this study provides a reliable gas recovery profile which guides the user in determining the amount of gas that can be recovered by a dual-horizontal well. The forward network is capable of predicting the gas recovery profile, cumulative production rate profile and the gas rate profile for the selected reservoir properties in less than 10 seconds as compared to run time of 30 minutes by a commercial simulator. Monte Carlo simulation, which implemented in this study, calculates the probabilities of the recovered amount of gas for a number of random well configuration combinations. Monte Carlo simulation provides the user with the opportunity to find the maximum amount that can be recovered from a given reservoir properties within 30 seconds.

The inverse network developed in this study predicts the well configuration parameters to achieve a desired recovery profile from a reservoir under consideration. The inverse network compares a large number of configurations in less than 10 seconds in order to predict the well configuration parameters that will achieve the desired recovery comparing to hours by the commercial reservoir simulators.

8.2 CONCLUSION

Using the Artificial Neural Networks (ANN) in predicting the recovered amount of the gas in place over a certain period of time in a few seconds was the main goal of this study. A total of 1250 random combinations of the reservoir properties and dual horizontal well configuration parameters, within the selected limits, have been generated in order to generate the gas recovery profiles using a commercial reservoir simulator. The generated properties and the dependent gas recovery profile have been used to generate two artificial networks forward network and inverse network. By optimizing the number of hidden layers, the number of neurons and the transfer function, a satisfied forward network and inverse network have been generated. Numbers of tests and validation methods have been used to validate the networks and achieve a full satisfaction. A Graphical user interface has been generated to give the user the opportunity of using the networks faster and easier.

8.3 RECOMMENDATIONS

This work can be further improved by incorporation of the following:

- Study a different range of properties as this study covers a specified limit of reservoir properties.
- This work studied a single porosity homogenous gas reservoir and the work can be extended by studying a dual-porosity gas reservoir.
- Dual horizontal well was the selected well configuration for this study and the work can extended to cover different multilateral wells like three horizontal and fish bone horizontal wells structure.
- A single-phase gas reservoir was selected for this study and the work can be extended to cover the oil reservoirs as well.

REFERENCES

1. Abraham, A. (2004) Meta-Learning Evolutionary Artificial Neural Networks, Neurocomputing Journal, Vol. 56c, Elsevier Science, Netherlands, (1–38).
2. Leslie, H., Darbonne, N and Monique, B.2005" Tight Gas", A supplement to Oil and Gas Investor 3-10, March
3. S.S. Lee, SPE, and C.A.M. Veeken, SPE, and Ante M. Frens, SPE, Sarawak Shell Berhad (2001) “Multi-Lateral Well Modeling to Optimize Well Design and Cost”, SPE 68728.
4. Howard Demuth, Mark Beale and Martin Hogan (2009): “Neural Networks Toolbox 6 User’s Guide,”
5. Internet Home Page: *http://www.mathworks.com*
6. Steve Bosworth, Hussein Saad, Gamal Ismail,Herve Ohmer, Mark Stracke, chris West and Albertus Retnano (1998) “Key Issue in Multilateral Technology”
7. Sada Joshi, Joshi Technology International, Inc. (2007) “Horizontal And Multilateral Well Technology”.
8. B. Guler, T. Ertekin, A. S. Grader, Pennsylvannia State University (1999) “An Artificial Neural Network Based Relative Permeability Predictor”
9. A. Centilmen, T. Ertekin, and A. S. Grader, The Pennsylvania State University (1999) “Applications of Neural Networks in Multiwell Field Development”
10. N. Silpngarmlers, B. Guler, T. Ertekin, A.S. Grader, Penn State U. (2001) “Development and Testing of Two-Phase Relative Permeability Predictors Using Artificial Neural Networks”

11. N. Silpngarmlers, T. Ertekin, The Pennsylvania State University (2002) “Artificial Neural Network Architectures for Predicting Two-Phase and Three-Phase Relative Permeability Characteristics”
12. L.F. Ayala, SPE, and T. Ertekin, SPE, Pennsylvania State U. (2005) “Analysis of Gas-Cycling Performance in Gas/Condensate Reservoirs Using Neuro-Simulation”
13. B. Basbug and Z. Karpyn, Pennsylvania State U.(2007) “Estimation of Permeability from Porosity, Specific Surface Area, and Irreducible Water Saturation using an Artificial Neural Network”
14. K. Srinivasan and T. Ertekin, Pennsylvania State University (2008) “Development and Testing of an Expert System for Coalbed Methane Reservoirs Using Artificial Neural Networks”
15. A. Ramgulam, T. Ertekin and P.B. Flemings, Pennsylvania State U (2007) “Utilization of Artificial Neural Networks in the Optimization of History Matching”

APPENDX (A)

The properties of the tested samples for the forward network

Property	Sample Test NO.1 (Figure 5.3)	Sample Test NO.2 (Figure 5.4)	Sample Test NO.3 (Figure 5.5)	Sample Test NO.4 (Figure 5.6)
Permeability vertical	0.059984 md	0.057267 md	0.08056 md	0.002074 md
Permeability horizontal	0.420098 md	0.431787 md	0.231864 md	0.254495 md
Porosity	.14661	0.217525	0.147613	0.20322
Rock compressibility	6.23E-07	9.47E-07	1.48E-07	1.99E-07
Reservoir thickness	71.99366 Ft	229.637 Ft	240.9398 Ft	82.0782 Ft
Reservoir depth	5565.097 Ft	5800.001 Ft	3574.745 Ft	3578.89 Ft
Initial pressure	7870.111 psi	6313.254 psi	3665.792 psi	2923.719 psi
Temperature	201.2023^0F	229.0517^0F	175.7536^0F	116.807^0F
Gas gravity	.6	0.525794	0.526445	0.55
Pattern Size	145161 acre	616 acre	254.61 acre	474.87 acre
Vertical distance for first branch	45.81415 Ft	146.1327 Ft	131.4217 Ft	52.23158 Ft
Horizontal length for first branch	45.81415 Ft	20.87609 Ft	65.71087 Ft	44.76993 Ft
Vertical distance for second branch	1909.822 Ft	1883.644 Ft	605.5106 Ft	1240.398 Ft
Horizontal length for second branch	763.9288 Ft	2354.556 Ft	1211.021 Ft	2067.331 Ft
Phase angle	180^0	90^0	180^0	135^0

APPENDIX (B)

The properties of the 50-case study tested samples for the forward network

Property	Tested Sample with error<5% (Figure 5.8)	Tested Sample with 10>error>5% (Figure 5.9)	Tested Sample with 15>error>10% (Figure 5.10)	Tested Sample with error>15% (Figure 5.11)
Permeability vertical	0.081491 md	0.017202 md	0.00328 md	0.009803 md
Permeability horizontal	0.276749 md	0.473816 md	0.830998 md	0.917276 md
Porosity	0.090815	0.212013	0.233023	0.087652
Rock compressibility	5.87E-07	5.54E-07	7.07E-07	3.20E-07
Reservoir thickness	339.9432 Ft	233.9239 Ft	167.9953 Ft	149.786 Ft
Reservoir depth	7778.531 Ft	3186.859 Ft	6464.446 Ft	7428.333 Ft
Initial pressure	7051.147 psi	3405.405 psi	5455.537 psi	5882.199 psi
Temperature	210.9755^{0}F	128.7977^{0}F	214.2027^{0}F	231.748^{0}F
Gas gravity	0.670143	0.696461	0.616289	0.503397
Pattern Size	149.33 acre	1,586.34 acre	68.53 acre	2,700.32 acre
Vertical distance for first	61.80785 Ft	148.8607 Ft	76.36149 Ft	40.85074 Ft
Horizontal length for first	123.6157 Ft	127.5949 Ft	61.0892 Ft	108.9353 Ft
Vertical distance for second	695.5903 Ft	3778.978 Ft	942.3843 Ft	1971.917 Ft
Horizontal length for second	1390 Ft	3020 Ft	628 Ft	1970 Ft
Phase angle	135^0	180^0	180^0	45^0

APPENDIX (C)

The properties of the 250-case study tested samples for the forward network

Property	Tested Sample with error<5% (Figure 5.13)	Tested Sample with 10>error>5% (Figure 5.14)	Tested Sample with 15>error>10% (Figure 5.15)	Tested Sample with error>15% (Figure 5.16)
Permeability vertical	0.060783 md	0.030417 md	0.002665 md	0.012575 md
Permeability horizontal	0.295714 md	0.13404 md	0.795045 md	0.901901 md
Porosity	0.136841	0.116491	0.247802	0.196473
Rock compressibility	4.41E-07	3.97E-08	4.4E-07	4.02E-07
Reservoir thickness	324.1342 Ft	272.9628 Ft	495.8748 Ft	321.3574 Ft
Reservoir depth	5088.55 Ft	2568.118 Ft	5905.012 Ft	7061.695 Ft
Initial pressure	5819.512 psi	2915.12 psi	7836.046 psi	6564.706 psi
Temperature	291.4398^{0}F	142.7096^{0}F	279.6719^{0}F	254.0162^{0}F
Gas gravity	0.51197	0.633927	0.682237	0.54298
Pattern Size	2,497.06 acre	686.3 acre	356.44 acre	1,148.68 acre
Vertical distance for first	235.7339 Ft	148.8888 Ft	45.07953 Ft	146.0716 Ft
Horizontal length for first	117.867 Ft	49.6296 Ft	225.3977 Ft	146.0716 Ft
Vertical distance for second	5688.748 Ft	1491.175 Ft	358.2136 Ft	1929.173 Ft
Horizontal length for second	4740.624 Ft	1491.175 Ft	1791.068 Ft	1286.115 Ft
Phase angle	45^0	135^0	90^0	135^0

APPENDIX (D)

The properties of the 500-case study tested samples for the forward network

Property	Tested Sample with error<5% (Figure 5.18)	Tested Sample with 10>error>5% (Figure 5.19)	Tested Sample with 15>error>10% (Figure 5.20)	Tested Sample with error>15% (Figure 5.21)
Permeability vertical	0.06619 md	0.090698 md	0.029723 md	0.000209 md
Permeability horizontal	0.535586 md	0.683382 md	0.991851 md	0.534436 md
Porosity	0.061044	0.15499	0.190578	0.114609
Rock compressibility	6.20E-07	4.74E-07	2.02E-07	2.92E-07
Reservoir thickness	431.6584 Ft	373.464 Ft	200.4156 Ft	184.4725 Ft
Reservoir depth	4171.119 Ft	6600.608 Ft	7895.416 Ft	6529.416 Ft
Initial pressure	2987.619 psi	5009.915 psi	6535.723 psi	6404.199 psi
Temperature	173.4481^0F	293.8207^0F	236.2533^0F	275.7198^0F
Gas gravity	0.518382	0.548263	0.695479	0.667842
Pattern Size	2,515.01 acre	1,215.24 acre	149.54 acre	302.58 acre
Vertical distance for first	3033.541 Ft	2400.221 Ft	6459.886 Ft	3561.5 Ft
Horizontal length for first	1895.963 Ft	1800.166 Ft	6459.886 Ft	3561.5 Ft
Vertical distance for second	651.5264 Ft	2645.711 Ft	928.0783 Ft	1980.277 Ft
Horizontal length for second	1950 Ft	1980 Ft	1390 Ft	1650 Ft
Phase angle	90^0	45^0	45^0	90^0

APPENDIX (E)

The properties of the 50-case study tested samples for the inverse network

Property	Tested Sample with error<5% (Figure 6.3)	Tested Sample with 10>error>5% (Figure 6.4)	Tested Sample with 15>error>10% (Figure 6.5)	Tested Sample with error>15% (Figure 6.6)
Permeability vertical	0.081491 md	0.091582 md	0.004713 md	0.069513 md
Permeability horizontal	0.276749 md	0.139486 md	0.550174 md	0.757443 md
Porosity	0.090815	0.249266	0.110123	0.225166
Rock compressibility	5.87E-07	5.34E-08	8.13E-07	6.35E-07
Reservoir thickness	339.9432 Ft	126.8186 Ft	370.0471 Ft	183.5041 Ft
Reservoir depth	7778.531 Ft	6078.368 Ft	4879.533 Ft	5705.998 Ft
Initial pressure	7051.147 psi	6107.596 psi	4208.802 psi	6592.617 psi
Temperature	210.9755 ^{0}F	269.6433 ^{0}F	106.1591 ^{0}F	221.7563 ^{0}F
Gas gravity	0.670143	0.68017	0.616018	0.672542

APPENDIX (F)

The properties of the 250-case study tested samples for the inverse network

Property	**Tested Sample with error<5% (Figure 6.8)**	**Tested Sample with 10>error>5% (Figure 6.9)**	**Tested Sample with 15>error>10% (Figure 6.10)**	**Tested Sample with error>15% (Figure 6.11)**
Permeability vertical	0.095413 md	0.030417 md	0.007567 md	0.060783 md
Permeability horizontal	0.832256 md	0.13404 md	0.319708 md	0.295714 md
Porosity	0.083731	0.116491	0.185327	0.136841
Rock compressibility	6.90E-07	3.97E-08	5.00E-07	4.41E-07
Reservoir thickness	345.7324 Ft	272.9628 Ft	430.6279 Ft	324.1342 Ft
Reservoir depth	7840.479 Ft	2568.118 Ft	5057.88 Ft	5088.55 Ft
Initial pressure	7591.603 psi	2915.12 psi	5066.819 psi	5819.512 psi
Temperature	283.1781 ^{0}F	142.7096 ^{0}F	260.1409 ^{0}F	291.4398 ^{0}F
Gas gravity	0.529562	0.633927	0.542009	0.51197

APPENDIX (G)

The properties of the 500-cases tested samples for the inverse network

Property	Tested Sample with error<5% (Figure 6.13)	Tested Sample with 10>error>5% (Figure 6.14)	Tested Sample with 15>error>10% (Figure 6.15)	Tested Sample with error>15% (Figure 6.16)
Permeability vertical	0.080611 md	0.021568 md	0.094112 md	0.003595 md
Permeability horizontal	0.515342 md	0.334222 md	0.59527 md	0.934006 md
Porosity	0.082301	0.090945	0.160615	0.189592
Rock compressibility	2.50E-07	9.91E-07	1.73E-07	7.21E-07
Reservoir thickness	179.6694 Ft	272.1411 Ft	193.7376 Ft	350.0731 Ft
Reservoir depth	3533.774 Ft	6682.72 Ft	3666.86 Ft	2287.966 Ft
Initial pressure	3628.887 psi	6135.493 psi	3014.755 psi	3128.29 psi
Temperature	116.305 ^{0}F	283.937 ^{0}F	111.3691 ^{0}F	141.3853 ^{0}F
Gas gravity	0.567146	0.693531	0.652014	0.538829

APPENDIX (H)

The Reservoir Simulator Data File

```
INUNIT FIELD

WSRF WELL 1

WSRF GRID TIME

WSRF SECTOR TIME

OUTSRF WELL LAYER NONE

OUTSRF RES ALL

OUTSRF GRID SO SG SW PRES OILPOT BPP SSPRES WINFLUX

WPRN GRID 0

OUTPRN GRID NONE

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 11 11 11

KDIR DOWN

DI IVAR

 11*206.6863
```

DJ JVAR

11*206.6863

DK ALL

1331*44.09643

DTOP

121*2625.518

**$ Property: Permeability I (md)   Max: 0.13039 Min: 0.13039

PERMI CON   0.13039

**$ Property: NULL Blocks Max: 1 Min: 1

**$ 0 = null block, 1 = active block

NULL CON   1

**$ Property: Porosity Max: 0.134022 Min: 0.134022

POR CON   0.134022

**$ Property: Permeability J (md)   Max: 0.13039 Min: 0.13039

PERMJ CON   0.13039

**$ Property: Permeability K (md)   Max: 0.0230373 Min: 0.0230373

PERMK CON   0.0230373

**$ Property: Pinchout Array Max: 1 Min: 1

**$ 0 = pinched block, 1 = active block

PINCHOUTARRAY CON   1

CPOR   7.949135e-007

MODEL GASWATER

TRES 1.759688e+002

PVTG ZG 1

**$ p	Z	visg
14.7	0.998801	0.0123581
120	0.990325	0.012394
240	0.980918	0.0125049
360	0.97181	0.0126448
480	0.96303	0.012782
600	0.954611	0.0130079
720	0.946584	0.0132664
840	0.938984	0.0135031
960	0.931842	0.0136881
1080	0.925192	0.0138182
1200	0.919063	0.0140181
1320	0.913485	0.0142123
1440	0.908484	0.0144063
1560	0.904082	0.0146188
1680	0.900297	0.0148491
1800	0.897143	0.0150961
1920	0.894629	0.0153589
2040	0.892757	0.0156365
2160	0.891526	0.0159278
2280	0.890929	0.016231
2400	0.890955	0.0165441
2520	0.891588	0.0168652

2640	0.89281	0.0171924
2760	0.8946	0.0175239
2880	0.896933	0.0178585
3000	0.899784	0.018196
3120	0.903129	0.0185361
3240	0.90694	0.0188786
3360	0.911192	0.0192232
3480	0.915859	0.0195695
3600	0.920915	0.0199175
3720	0.926336	0.0202667
3840	0.9321	0.0206169
3960	0.938184	0.0209679
4080	0.944567	0.0213194
4200	0.951229	0.021671
4320	0.958153	0.0220222
4440	0.96532	0.0223724
4560	0.972714	0.0227211
4680	0.98032	0.0230677
4800	0.988123	0.0234116
4920	0.996111	0.0237524
5040	1.00427	0.0240894
5160	1.01259	0.0244221
5280	1.02106	0.02475
5400	1.02967	0.0250724

5520	1.03841	0.025389
5640	1.04727	0.0257002
5760	1.05624	0.0260062
5880	1.06532	0.0263077
6000	1.0745	0.0266049

BWI 1.002

CVW 0.0

CW 3.26282e-006

DENSITY WATER 62.7112

REFPW 14.696

VWI 0.964115

GRAVITY GAS 6.007822e-001

ROCKFLUID

RPT 1

**$ Sw krw

SWT

0.15	0
0.175	0
0.2	0
0.225	0
0.25	0
0.275	0.000103
0.3	0.000668
0.325	0.001995

0.35	0.004338
0.375	0.007925
0.4	0.012965
0.425	0.019658
0.45	0.028191
0.475	0.038746
0.5	0.051496
0.525	0.066609
0.55	0.084248
0.575	0.104573
0.6	0.127737
0.625	0.153893
0.65	0.183188
0.675	0.215767
0.7	0.251773
0.725	0.291345
0.75	0.334621
0.775	0.381737
0.8	0.432827
0.825	0.48802
0.85	0.547448
0.875	0.611238
0.9	0.679518
0.925	0.75241

```
        0.95        0.830041
        0.975        0.91253
        1        1
**$        Sg        krg
SGT
        0        0
        0.025        0
        0.05        0
        0.075        0
        0.1        1e-006
        0.125        7e-006
        0.15        3.1e-005
        0.175        9.3e-005
        0.2        0.000232
        0.225        0.000501
        0.25        0.000977
        0.275        0.00176
        0.3        0.00298
        0.325        0.0048
        0.35        0.007416
        0.375        0.011065
        0.4        0.016028
        0.425        0.022631
        0.45        0.03125
```

```
    0.475      0.042315
    0.5      0.056314
    0.525      0.073794
    0.55      0.095367
    0.575      0.121716
    0.6      0.15359
    0.625      0.191818
    0.65      0.237305
    0.675      0.291038
    0.7      0.354093
    0.725      0.427631
    0.75      0.512909
    0.775      0.61128
    0.8      0.724196
    0.825      0.853215
    0.85      1
INITIAL
VERTICAL DEPTH_AVE WATER_GAS EQUIL NOTRANZONE

REFDEPTH 2.625518e+003
REFPRES 3.767695e+003
DWGC 10000
NUMERICAL
RUN
```

```
DATE 2011 1 1
        WELL  'Well-1'
PRODUCER 'Well-1'
OPERATE  MIN  BHP  100.  STOP
**$        rad  geofac  wfrac  skin
GEOMETRY  I  0.25  0.37  1.  0.
PERF  GEOA  'Well-1'
**$ UBA    ff  Status  Connection
  6 6 2  1.  OPEN    FLOW-TO  'SURFACE'  REFLAYER
  7 6 2  1.  OPEN    FLOW-TO  1
  8 6 2  1.  OPEN    FLOW-TO  2
  9 6 2  1.  OPEN    FLOW-TO  3
  6 6 9  1.  OPEN    FLOW-TO  1
  5 5 9  1.  OPEN    FLOW-TO  5
  4 4 9  1.  OPEN    FLOW-TO  6
  3 3 9  1.  OPEN    FLOW-TO  7
DATE 2012 1  1.00000
DATE 2013 1  1.00000
DATE 2014 1  1.00000
DATE 2015 1  1.00000
DATE 2016 1  1.00000
DATE 2017 1  1.00000
DATE 2018 1  1.00000
DATE 2019 1  1.00000
```

DATE 2020 1 1.00000

DATE 2021 1 1.00000

DATE 2022 1 1.00000

DATE 2023 1 1.00000

DATE 2024 1 1.00000

DATE 2025 1 1.00000

DATE 2026 1 1.00000

DATE 2027 1 1.00000

DATE 2028 1 1.00000

DATE 2029 1 1.00000

DATE 2030 1 1.00000

DATE 2031 1 1.00000

DATE 2032 1 1.00000

DATE 2033 1 1.00000

DATE 2034 1 1.00000

DATE 2034 2 1.00000

DATE 2035 1 1.00000

DATE 2036 1 1.00000

DATE 2037 1 1.00000

DATE 2038 1 1.00000

DATE 2039 1 1.00000

DATE 2040 1 1.00000

DATE 2040 2 1.00000

DATE 2041 1 1.00000

DATE 2042 1 1.00000

DATE 2043 1 1.00000

DATE 2044 1 1.00000

DATE 2045 1 1.00000

DATE 2046 1 1.00000

DATE 2047 1 1.00000

DATE 2048 1 1.00000

DATE 2049 1 1.00000

DATE 2050 1 1.00000

DATE 2050 2 1.00000

DATE 2051 1 1.00000

DATE 2052 1 1.00000

DATE 2053 1 1.00000

DATE 2054 1 1.00000

DATE 2055 1 1.00000

DATE 2056 1 1.00000

DATE 2057 1 1.00000

DATE 2058 1 1.00000

DATE 2059 1 1.00000

DATE 2060 1 1.00000

STOP