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John and Willie Leone Family Department of Energy and Mineral Engineering

DEVELOPMENT AND UTILIZATION OF INTEGRATED ARTIFICIAL EXPERT SYSTEMS FOR DESIGNING MULTI-LATERAL WELL CONFIGURATIONS, ESTIMATING RESERVOIR PROPERTIES AND FORECASTING RESERVOIR PERFORMANCE

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Abstract

Reservoir simulation is one of the main tools if not the most important one reservoir engineers use to forecast a reservoir performance. Nevertheless, developing and operating a reservoir simulator in the first place can be an arduous task that requires a set of highly skilled individuals in science, advanced mathematics, programing, and reservoir engineering and powerful computational models.

The reliability of a reservoir simulator depends on the availability and the quality of the reservoir properties. These properties are obtained from open-hole logs, core studies and well testing analysis which can sometimes be prohibitively cost intensive.

Another important component of the overall process affecting the reservoir performance is the multilateral well configuration. Achieving the right design of a multilateral well configuration is a complex problem due to the vast possibilities of well forms that need to be evaluated.

In light of the above, this dissertation demonstrates the development and the application of a set of integrated artificial expert systems in the area of forecasting, reservoir evaluation and multilateral well design. The applied method has gradually progressed in degrees of complexity from addressing a preliminary case of volumetric single phase gas reservoirs completed with only dual-laterals towards an expanded form of the same system with varying multi-laterals and reservoir properties to eventually and successfully implementing it to multiphase reservoirs with bottom water drive systems completed with multi-laterals (choice of 2-5 laterals). The developed method and tools cover a wide spectrum of rock and fluid properties spanning tight to conventional sands. The developed approach successfully delivers a total of five distinct artificial

expert systems, three of them serve as proxies to the conventional numerical simulator for predicting reservoir performance in terms of cumulative oil recovery, cumulative oil and gas productions and estimating the end of plateau and abandonment times and a third one for predicting cumulative fluid production. These aforementioned systems are categorized as forward-looking solutions. Whereas the other two artificial expert systems are categorized as inverse-looking solutions, one that addresses the multi-lateral well design problem and the other that estimates critical reservoir properties that can be used at the very least as first estimators in assist history matching problems and for improving the assessment of nearby prospects in field development or in-fill drilling exercises.

Furthermore, graphical user interfaces (GUIs) in conjunction with the expert systems structured are developed and assembled together for standalone installation. These GUIs allow the engineer to edit and input data, produce results numerically and graphically, compare results with a commercial numerical simulator, and generate an interactive 3-D visualization of the multilateral well.

It is expected that the developed integrated artificial expert systems will immensely reduce expenses and time requirements and effectively enhance the overall decision-making process. However, it is worth noting that the proposed expert systems are not to replace the conventional and well established procedures and protocols but rather as auxiliary or complementary applications, where applicable, to relief some of the computational overhead, provide educated estimation of key reservoir properties or the very least help fine tune them and present the inverse-looking solution to the multi-lateral well design problem or the least a starting point.

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Chapter 1 Introduction

Ever since the first gusher of oil; petroleum engineers are establishing, improving and innovating many processes and tools in order to enhance their decision-making capabilities. Managing reservoirs in the most cost-effective manner towards achieving their maximum potentials is the ultimate goal. This dissertation aspires to be a step in the right direction. In this research a set of integrated artificial expert systems were developed in the area of forecasting, reservoir evaluation and multilateral well design.

One of the main processes used by reservoir engineers is reservoir simulation. Reservoir simulators are mainly used to predict the performance of hydrocarbon reservoirs. The results obtained are instrumental to the economic evaluation of a particular reservoir. The outcomes will yield validity for or against developing a certain field or modifying pre-existing conditions such as production targets. Nevertheless, developing and operating a reservoir simulator tool in the first place is a laborious task that requires a set of highly skilled individuals in science, advanced mathematics, programing, and reservoir engineering and powerful computational models **(Ertekin, et al., 2001)**. Once the governing equations and methodologies have been established for a reservoir simulator, a simulation study will still require tailoring and fine tuning of that simulator to a specific reservoir, in other words it is not a one size that fits all. In order to properly conduct a simulation study, key rock and fluid properties and parameters are required for customizing a reservoir simulator. These must have properties are obtained through another very important reservoir engineering process known as reservoir evaluation.

Reservoir evaluation is the identification and estimation of reservoir properties and its prospects. Engineers and scientists interpret certain properties using different tools and methods.

For example, open-hole logs and fluid sampling are used for determining fluid properties, types and contacts; core analysis is applied to obtain geo-mechanical and petro-physical properties; and pressure transient analysis of buildup and drawdown tests are used for estimating formation permeability, reservoir boundaries and initial reservoir pressure just to name a few. Such properties are significant for the success of any simulation study in order to customize a reservoir simulator to mimic reality as accurate as possible. Obtaining such information requires a strong commitment and a huge investment in terms of cost, manpower and time. Therefore, considering the study objectives a simulation study may not be feasible **(Ertekin, et al., 2001)**. On the other hand, given that a simulation study is warranted another important component of the overall process affecting the reservoir performance is the multilateral well configuration.

With the advancement in drilling technology; drilling horizontal, dual laterals or even multi-lateral wells are becoming a normal trend. These well types have proven to increase recovery from a drainage area, improve sweep efficiency, and elongate well life by delaying water coning or gas cusping; especially in tight and thin reservoirs. However, due to the higher initial capital investment and future complicated remedial work and maintenance of these wells compared to vertical wells, the placement and configuration strategies for these wells are of great importance to gain the highest possible rate of returns on investment. When planning such wells, reservoir engineers rely on different techniques for their risk analysis depending on the level of field maturity, quality of the reservoir description, and field development constraints such as well spacing. For a prolific brown (mature) field with good reservoir description, the reservoir engineer experience and intuition could help guide the placement and configuration of a multi-lateral well. On the other hand, green (immature) fields with limited reservoir description;

require higher computational efforts for many different possible scenarios using reservoir simulators to aid the reservoir's engineer decision.

In light of the above, this dissertation demonstrates the development and the application of a set of integrated artificial expert systems in the area of forecasting, reservoir evaluation and multilateral well design. The applied method has gradually progressed in degrees of complexity from addressing a preliminary case of volumetric single phase gas reservoirs completed with only dual-laterals towards an expanded form of the same system with varying multi-laterals and reservoir properties to eventually and successfully implementing it to multiphase reservoirs with bottom water drive systems completed with multilateral (choice of 2-5 laterals). The developed method and tools cover a wide spectrum of rock and fluid properties spanning tight to conventional sands. The developed approach successfully delivers a total of five distinct artificial expert systems, three of them serve as proxies to the conventional numerical simulator for predicting reservoir performance in terms of cumulative oil recovery, cumulative oil and gas productions and estimating the end of plateau and abandonment times and a third one for predicting cumulative fluid production. These aforementioned systems are categorized as forward-looking solutions. Whereas the other two artificial expert systems are categorized as inverse-looking solutions, one that addresses the multi-lateral well design problem and the other that estimates critical reservoir properties that can be used at the very least as first estimators in assist history matching problems and for improving the assessment of nearby prospects in field development or in-fill drilling exercises.

Furthermore, graphical user interfaces (GUIs) in conjunction with the expert systems structured are developed and assembled together for standalone installation. These GUIs allow the engineer to edit and input data, produce results numerically and graphically, compare results with a commercial numerical simulator, and generate an interactive 3-D visualization of the multilateral well.

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Chapter 2 Literature Review

2.1 Artificial Neural Network

2.1.1 Background

The development of artificial neural networks (ANNs) was inspired by the biological nervous system, similar to what we have in our bodies. In the biological neural network information is transferred between the cell bodies which are highly interconnected as illustrated in **Figure 2.1**. The message passes from the neuron's cell through the axon through the many synaptic connections at the end of the axon then through a very narrow synaptic space to the dendrites of the next neuron at an average exchange rate of 3 m/sec **(Graupe, 2007)**. Since each biological neuron consists of hundreds of synapses and hundreds of dendrites then it can send and receive to and from many other neurons, which explains the highly interconnectivity nature of the biological neural network **(Graupe, 2007)**.

McCulloch and Pitts introduced a simplified mathematical model of a biological neuron in 1943 **(McCulloch & Pitts, 1943)**. Rosenblatt then followed with his invention of the perceptron algorithm in 1957 **(Rosenblatt, 1957)**, however since it could not be trained to identify various patterns led to a recession in the area of neural network studies for many years. Interest in neural networks surged again in the 1980s when a famous book by Marvin Minsky and Seymour Papert was reprinted in 1987 as "*Perceptron – Expanded Edition*" correcting some of the errors introduced in the original book of 1969 "*Perceptron*" which led to the miss reception of neural networks **(Wikimedia Foundation, Inc, 2012)**.

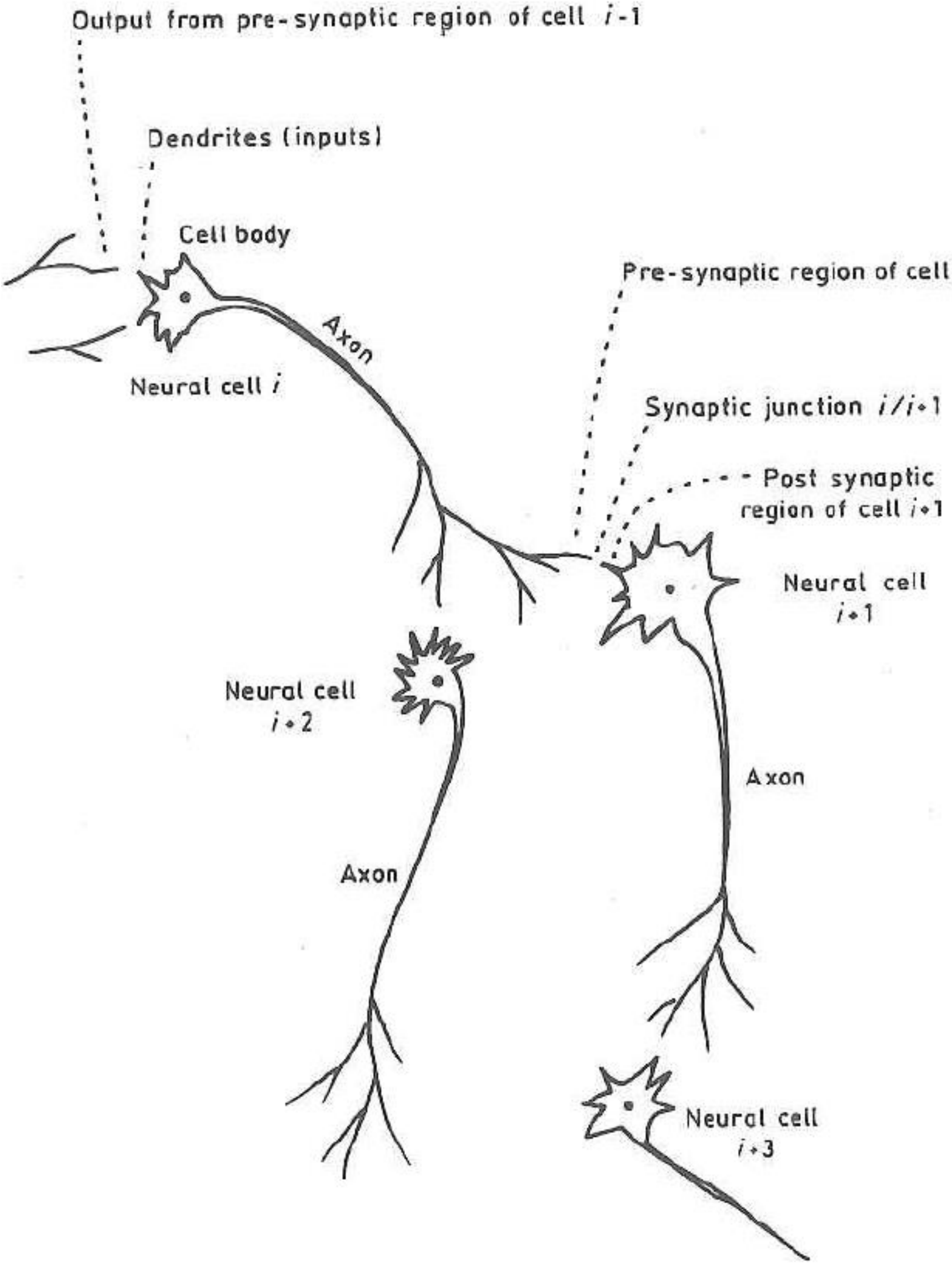


Fig. 2.1: Interconnection of biological neural networks (Graupe, 2007).

2.1.2 Definition

Artificial neural networks are computational networks that aspire to simulate, in a general manner, the biological nervous system as illustrated in **Figure 2.2**. The structure is set up of a huge number of elements working together which are highly interconnected. Mainly, neurons receive inputs from other sources, sums them up, perform a generally nonlinear operation on them, and then output the results.

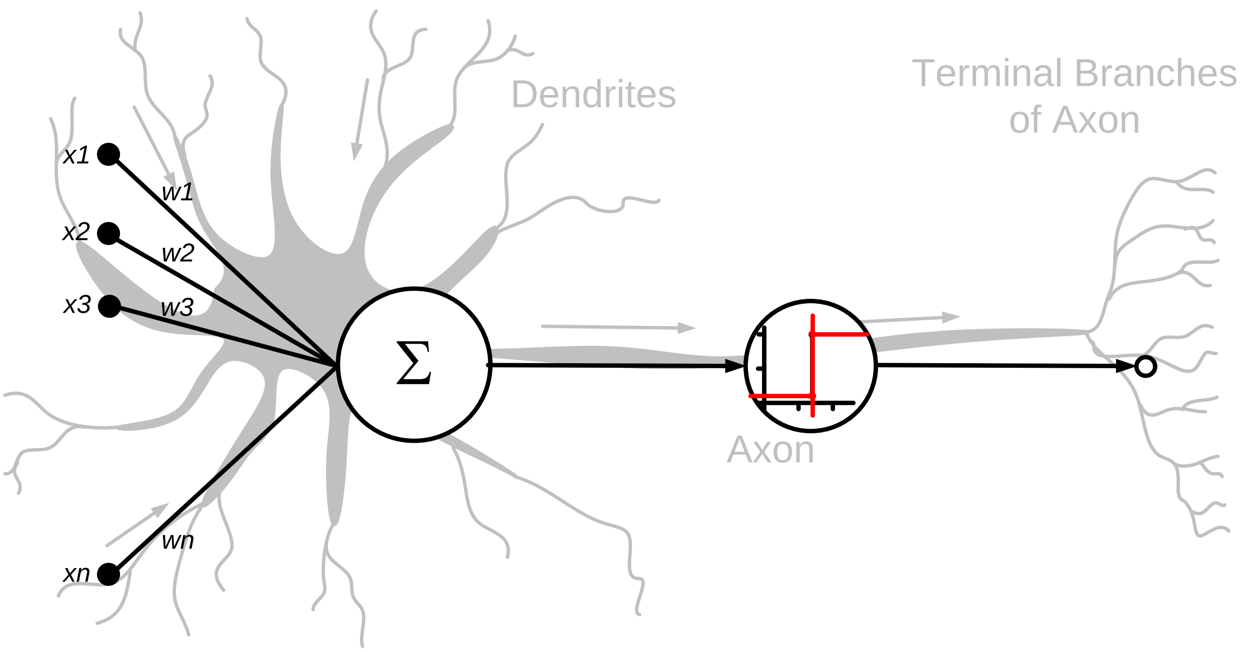


Fig. 2.2: A simple abstract of an ANN from a biological nerve (Nelson, 2012).

2.1.3 ANN vs. Conventional Models

ANNs are different than conventional numerical models that's objective is to accelerate computations for explicit problems relative to a human brain regardless to the order of computing elements and their structure. ANNs allow the use of basic mathematical operations such as additions and multiplications "to solve complex, mathematically ill-defined problems, nonlinear problems or stochastic problems" **(Graupe, 2007)**. Another powerful feature of ANNs is its highly parallel approach. Most conventional software follow a serial method which makes it vulnerable to any failure in the sequence consequently ending the process prematurely, whereas the parallelism capability of ANNs makes it insensitive to such malfunctions **(Graupe, 2007)**. Thus, ANNs were found to be very useful and powerful in pattern recognition, prediction, abstraction and interpretation of sporadic data.

2.1.4 Typical ANN Architecture

It is fundamental to the understanding of artificial neural networks to note that in a biological nervous system not all interconnections have the same influence. Some connections will have leverage over others and some will even work to prevent the passing of messages. This is due to the variances in chemistry and by the presence of chemical source and controlling matter inside or surrounding the neurons, the axons and in the synaptic connections **(Graupe, 2007)**.

A typical architecture of ANN consists of three main parts: an input layer, a hidden layer or layers and an output layer as shown in **Figure 2.3**. Each layer comprises a number of neurons depending on the definition of the problem. The layers are all interconnected. These interconnections are assigned weights and biases.

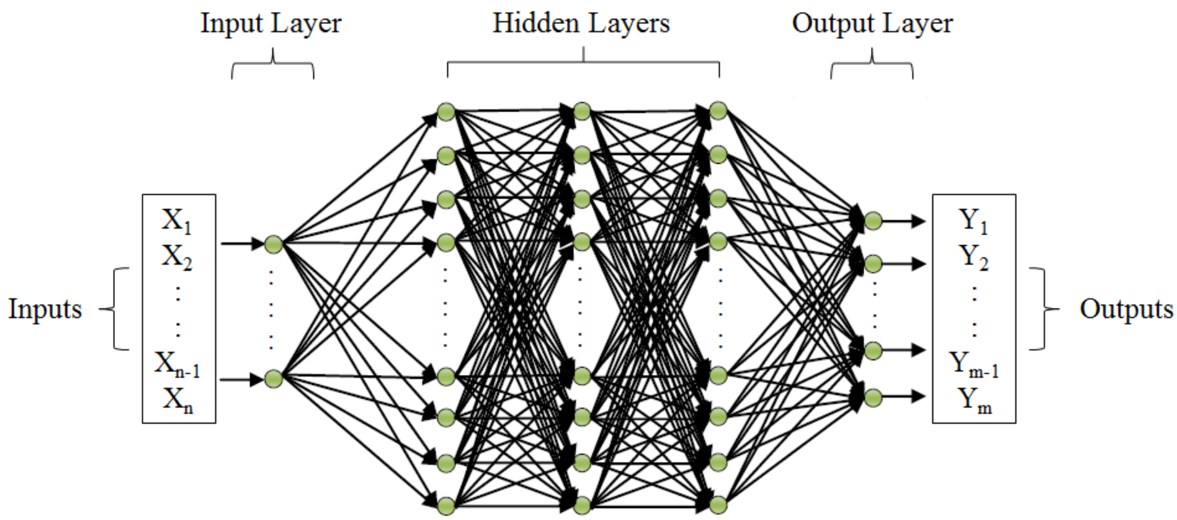


Fig. 2.3: A typical ANN architecture (Chidambaram, 2009).

2.1.5 Feedforward Backpropagation Neural Networks

The feedforward backpropagation approach is the artificial neural network engine used for this study. The term feedforward describes the flow of information from the input layer through the hidden layer or layers to the output layer, whereas the term backpropagation is an abbreviation for "backward propagation of errors". Backpropagation in broad terms is an algorithm with an iterative process that adjusts the weights of the links within the network in order to minimize the error between the predicted outputs of the net and the desired targets **(Rumelhart, et al., 1986)**. The overall process can mainly be described as follows. First, random weights and biases are assigned to the input parameters during initialization. Then the flow of information is carried out via transfer functions from the input layer through the hidden layer or layers to the output layer where the network results are produced. An error signal is then measured between the desired outputs and the results produced by the network. This error signal is then propagated backwards, hence the name backpropagation, from the output layer towards the hidden layer or layers with the purpose of adjusting the weights and biases based on the significance of the links in predicting the results. This process iterates until an acceptable error tolerance and/or predefined criteria are met, then it is said that the network is trained and can be used for solving for a new set of inputs.

2.1.6 Transfer Functions

This section will shed some light on some of the most commonly used transfer functions, which were also applied in this study. In a broad sense, when transfer functions are provided with a layer's net input vector (or matrix) N, it computes an output vector (or matrix) A. An example of a neuron with *R* inputs is illustrated in **Figure 2.4**, where each input *P* is assigned a random weight *w*, during initialization only, then summed up and added to a bias *b* which collectively forms the input *n* to the transfer function *f*.

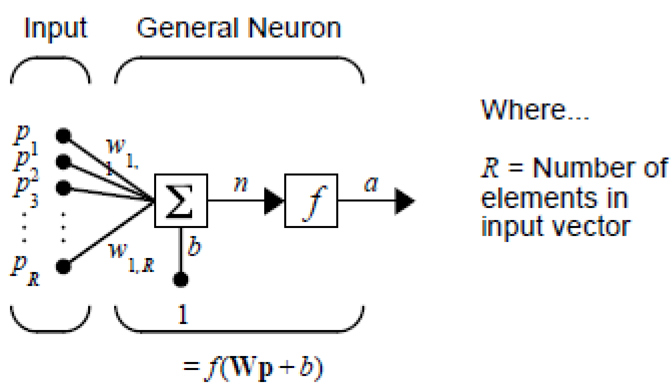


Fig. 2.4: A Neuron Model (Demuth & Beale, 2002).

The functions log-sigmoid, tan-sigmoid and linear are amongst the most commonly used transfer functions in multilayer neural networks. The log-sigmoid function produces values between 0 and 1 where the neuron's net input ranges from negative to positive infinity. Whereas the hyperbolic tangent sigmoid transfer function generates outputs between -1 and 1 as the neuron's net input varies from negative to positive infinity. The linear transfer function simply returns the value passed to it as indicated by equation 2-1.

$$a = purelin(n) = purelin(\mathbf{W}\mathbf{p} + b) = \mathbf{W}\mathbf{p} + b \qquad (2\text{-}1)$$

To apply backpropagation the implemented transfer functions must be differentiable. All of the above mentioned transfer functions have equivalent derivative functions. **Figure 2.5** illustrates a graphical depiction of the three transfer functions and **Table 2.1** provides some of the available transfer functions and their symbols in **MATLAB**®.

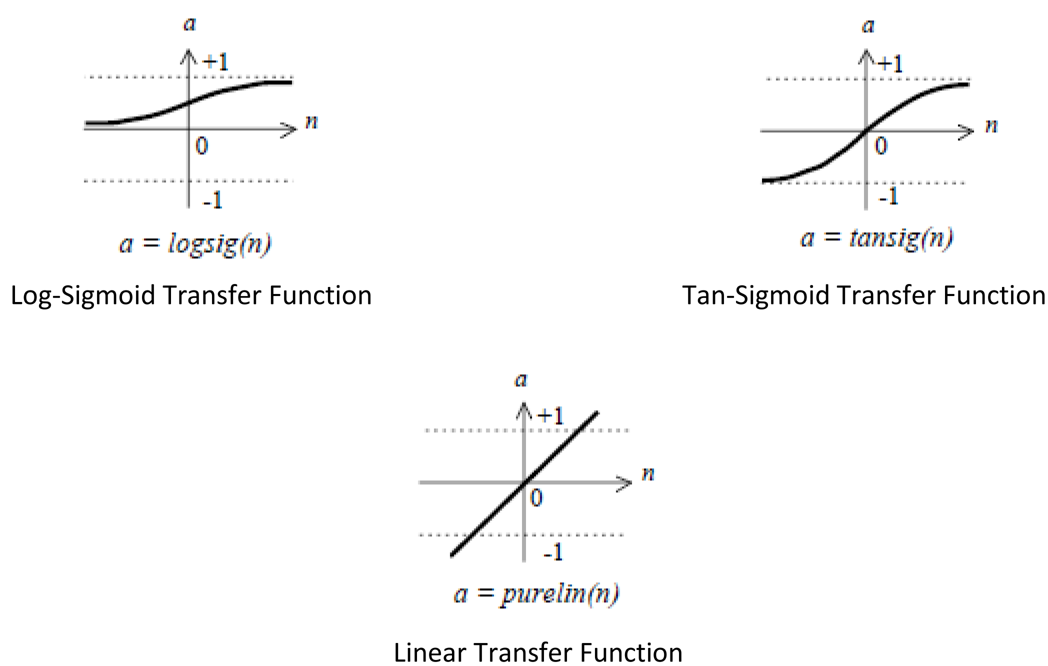
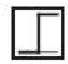
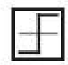
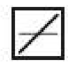
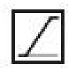
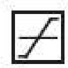
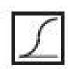
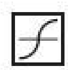
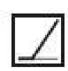


Fig. 2.5: Graphical Representations of the Most Common Transfer Functions (Demuth & Beale, 2002).

Table 2.1: Transfer Functions (reproduced from (Chidambaram, 2009))

Name	Input/Output Relation	Icon	MATLAB Function
Hard Limit	$a = 0 \quad n < 0$ $a = 1 \quad n \geq 0$		hardlim
Symmetrical Hard Limit	$a = -1 \quad n < 0$ $a = +1 \quad n \geq 0$		hardlims
Linear	$a = n$		purelin
Saturating Linear	$a = 0 \quad n < 0$ $a = n \quad 0 \leq n \leq 1$ $a = 1 \quad n > 1$		satlin
Symmetric Saturating Linear	$a = -1 \quad n < -1$ $a = n \quad -1 \leq n \leq 1$ $a = 1 \quad n > 1$		satlins
Log-Sigmoid	$a = \frac{1}{1 + e^{-n}}$		logsig
Hyperbolic Tangent Sigmoid	$a = \frac{e^n - e^{-n}}{e^n + e^{-n}}$		tansig
Positive Linear	$a = 0 \quad n < 0$ $a = n \quad 0 \leq n$		poslin
Competitive	$a = 1$ neuron with max n $a = 0$ all other neurons	C	compet

2.2 Petroleum Engineering Applications of Artificial Expert Systems

The field of petroleum engineering is no stranger to the applications of artificial expert systems. For many years now, dating back to the 1980's researchers have explored their potential and applicability to many petroleum engineering disciplines such as drilling, reservoir characterization, well testing, and reservoir simulation and enhanced oil recovery. A study listed several ANN applications in the oil and gas industry depending on the problem type as (1) pattern/cluster analysis, (2) signal/image processing, (3) control applications, (4) prediction and correlation, and (5) optimization **(Ali, 1994)**. This section will highlight some of the previous expert systems applications in various fields of petroleum engineering.

An actual field in West Texas bearing an unconventional oil reservoir was characterized using artificial expert systems. The developed expert systems were capable of generating synthetic well logs and identifying payzones. Averaged seismic data and detailed 3D seismic data were used to predict low-resolution and high-resolution well logs respectively. These artificially produced well logs were then used to identify payzones **(Gharehlo, 2012)**.

Production maps were also generated for the same field in West Texas by employing artificial expert systems. These expert systems were developed with the purpose of predicting quarterly cumulative production of oil, water and gas over a span of two years. The resulting production surfaces will guide the placement of new infill drilling. The results generated by the expert systems in comparison to the actual field performance showed close approximations. In addition, an optimization engine was developed to suggest the best fit for purpose well completion parameters to aid in developing the field in the most economic and efficient manner **(Bansal, 2011)**.

A neuro-simulation tool was developed using artificial neural network with the purpose of predicting reservoir properties. The network uses the reservoir production and pressure data to predict the reservoir porosity, permeability, thickness and endpoint saturations and relative permeability values. The development is believed to be instrumental in reducing simulation runs needed for obtaining an acceptable history match. Real field data from Perry reservoir located in Brayton Fields, west of Corpus Christi, Texas were subjected to the developed neuro-simulation tool. A good history match was obtained using the field production data **(Chidambaram, 2009)**.

An artificial neural network was successfully developed and implemented on an actual field study with the objective of predicting rates and optimizing the search of sweet spots for infill drilling. The study integrated existing well configurations, its completion and production history as well as seismic attributes to assemble the knowledge base for training the network. The study was able to correlate between production, completion data, interference effects, and reservoir characteristics drawn from seismic attributes. The developed ANN permitted creating spatial maps of gas production indicating potentially high productivity new locations with respect to the predicted initial rate and 10 year cumulative production criteria **(Thararoop, et al., 2008)**.

A web-based fuzzy expert system called (MULTSYS) was developed with the objective of assisting in the preliminary planning and completion of horizontal and multilateral wells. It follows a systematic approach, first screening for horizontal and multilateral candidates, if applicable then what completion type of the lateral section and then what junction levels. The developed system was tested on eight oil field cases collected from literature and successfully provided recommendations that were consistent with reality **(Garrouch, et al., 2005)**.

A study utilizing artificial neural networks for predicting two-phase, liquid/liquid and liquid/gas, relative permeability was conducted. Some relative permeability data were collected from literature to build the data base for training the networks whereas experimental data were used for testing and validating the developed ANNs. Five ANNs for the liquid/liquid relative permeability were developed utilizing different combinations of input parameters and functional links. The ANN with the highest degree of complexity and included all of the input parameters and functional links had the best predictions hence the smallest deviation from actual experimental data. In addition another ANN for liquid/gas relative permeability was developed and compared its predictions with the predictions produced by Corey's and Honarpour's correlations and the actual experimental data which indicated a good agreement of the ANN predictions with the other two **(Silpngarmlers, et al., 2002)**.

Another ANN development demonstrated its capability in estimating the initial pressure explicitly, and permeability and skin factor of oil reservoirs implicitly. Five sets of pressure build up data for conventional and dual porosity reservoirs were used to test the network which indicated predicted similar results produced using the Horner plot **(Jeirani & Mohebbi, 2006)**.

A novel utilization of ANNs was applied to develop a virtual well testing approach. The objective of the developed ANN was to predict pressure transient data at locations without performing an actual test, which in turn can be used for estimating reservoir characteristics with conventional methods **(Dakshindas, et al., 1999)**.

A proxy to the compositional simulator was developed using ANN to predict the gas condensate reservoir performance under gas cycling. Furthermore, another ANN was developed as an inverse-looking solution, where the amount of gas to be re-injected and the corresponding gas flow rate are determined given a target condensate recovery and gas recovery over a certain time **(Ayala H. & Ertekin, 2007)**.

2.3 Relevant Studies

A flexible simulation model was developed and utilized to determine the optimum multi-lateral configuration for different reservoir conditions and presented shape factors for different well configurations. The study investigated five configurations for three permeability anisotropies and inspected two different lateral lengths ratios **(Retnanto, et al., 1996)**

A hybrid Genetic Algorithm (GA) was developed in order to optimize the design for reservoir development. A commercial simulator that generated the input data, i.e. production schemes, and retrieved the output data, i.e. design parameters, from the optimizing algorithm were linked together. This process continued while evaluating the objective function, the Net Present Value (NPV) of the project, until the maximum NPV was achieved. This procedure was implemented on a real project design using two approaches. The first approach did not include the proposed solution by the project design team in the initial population of the hybrid genetic algorithm and the second approach did. Both approaches yielded improvements over the initial proposed solution; however the second approach resulted in higher profits **(Bittencourt & Horne, 1997)**.

The pressure transient behaviors of dual lateral wells were evaluated by developing an analytical solution used in Laplace domain for an oil bearing reservoir. Among the study effects of the dual lateral configuration parameters were analyzed. These parameters included the phase angle between the lateral legs, the lateral lengths, and horizontal and vertical separation between laterals. Some of these observations indicated that the pressure drop decreases as the phase angle increases. As the phase angle increases towards 90 degrees the differences in the well behavior decreases until it becomes insignificant for angles higher than 135 degrees. As the horizontal separation increases, the horizontal coverage of the reservoir increases and the dimensionless pressure decreases. For long periods, the influence of the vertical separation between the laterals is weak **(Ozkan, et al., 1998)**.

A general procedure for optimizing nonconventional well type, location, and trajectory by applying a Genetic Algorithm combined with a feed forward artificial neural network (ANN), a hill climber (HC), and a near-well upscaling method was developed. The GA was the main optimization application for the reservoir simulator, while the ANN was used to mimic the reservoir simulator for significantly reducing the number of simulation runs required. The hill climber was used to improve the search in the direct vicinity of the solution and the near-well upscaling technique was used to accelerate the finite-difference simulator run. A number of problems including different reservoir forms and fluid properties were subjected to the described method with the objective function of maximizing cumulative production or net present value (NPV) **(Yeten, et al., 2003)**.

Chapter 3 Problem Statement

The processes involved in field developments are many, interrelated, and cost and labor intensive. Many unknowns exist; however the risks are always high to allow for full field seismic surveys, drilling and testing exploration and delineation wells and conducting special core analysis without having hints about the prospects of the subject reservoir to justify additional spending. Therefore, reservoir engineers are challenged to make the most out of the few data collected.

One of the main tools necessary to aid a petroleum engineer's decisions is the numerical reservoir simulator. It provides long term forecasts on the deliverability of the reservoir under different field development scenarios and operating constraints which yields tremendous value to the engineer. However considering the vast number of different possible scenarios it is impractical to perform a simulation run for each and every possible combination. Hypothetically speaking to emphasize this point, considering a reservoir where it has a range of three possible values for each of the normal and two lateral permeabilities, hence a total of 9 permeability values to choose from and an option of three well configurations, and wanting to simulate the reservoir performance using eight different initial oil rates. The total amount of parameters available to choose from is 20, 9 permeability values, 3 well designs and 8 initial oil rates. For each run the engineer will combine 5 parameters, one from each category. The total number of possible combinations is found by equation 3-1:

$$\binom{n}{k} = \frac{n!}{k!(n-k)!} \quad \text{, where } 0 \le k \le n \qquad (3\text{-}1)$$

Where *n* is the total number of parameters available and *k* is the number of combined categories, which is in this case 20 and 5 respectively. Hence the total number of five distinct combinations is 15504 possible scenarios.

$$\binom{20}{5} = \frac{20!}{5!\,15!} = 15504$$

If on average it takes about 10 minutes to run each case it would take about 108 days with the simulator running continuously 24/7 to go through all of the 15504 possible scenarios which is absolutely unreasonable and unrealistic. Therefore, there is a need for a proxy to the numerical simulator that runs at a fraction of the time required by the simulators and less labor intensive when preparing the input files.

Another challenging aspect is coming up with a fit for purpose multi-lateral well design. Given the major advancements in drilling technology, drilling horizontal and even multi-lateral wells are becoming new norms due to their advantages over vertical wells. However this adds to the complexity of the problem since vast possibilities exist. The current numerical simulators can only address this problem from a forward-looking view point, heuristically via trial and error approach where different well designs are predefined then the simulator predicts its performance and this cycle continues until a satisfactory performance based on the developer's criteria is met. This procedure is time and labor intensive and tremendously increases the computational cost. Hence it requires addressing it with an inverse-looking approach, where by given the target reservoir performance with defined reservoir properties a multi-lateral well design is suggested. From that point onwards an engineer can improve on the recommended design or modify it to adhere to certain field, cost or operational constraints.

It is from reservoir engineering best practices to continuously quality-check a numerical simulator against actual field performances and fine tuning it if needed to successfully match existing actual productions and pressure distributions. This is known as history matching, where adjustments to a numerical simulator are made by introducing permeability multipliers and/or adjusting fluid saturations and few or more of the rock and fluid properties until a match is met. However most of the time, these type of modifications are up to the discretion of the responsible engineer rather than relying on gathering hard data from special core analysis studies, well testing, fluid sampling and open and cased hole logs. This is arguably understood due to the expensive invoice involved in obtaining such data. Nevertheless, different engineers with different backgrounds and years of experience will produce different judgments. Hence the need for an intelligent system that can produce at the very least a first educated guess of suggested modifications.

With respect to the above, this dissertation demonstrates the development and the application of a set of integrated artificial expert systems in the area of forecasting, reservoir evaluation and multilateral well design. The applied method has gradually progressed in degrees of complexity from addressing a preliminary case of volumetric single phase gas reservoirs completed with only dual-laterals towards an expanded form of the same system with varying multi-laterals and reservoir properties to eventually and successfully implementing it to multiphase reservoirs with bottom water drive systems completed with multilateral (choice of 2-5 laterals). The developed method and tools cover a wide spectrum of rock and fluid properties spanning tight to conventional sands. The developed approach successfully delivers a total of five distinct artificial expert systems, three of them serve as proxies to the conventional numerical simulator for predicting reservoir performance in terms of cumulative oil recovery, cumulative oil and gas productions and estimating the end of plateau and abandonment times and a third one for predicting cumulative fluid production. These aforementioned systems are categorized as forward-looking solutions. Whereas the other two artificial expert systems are categorized as inverse-looking solutions, one that addresses the multi-lateral well design problem and the other that estimates critical reservoir properties that can be used at the very least as first estimators in assist history matching problems and for improving the assessment of nearby prospects in field development or in-fill drilling exercises.

Furthermore, graphical user interfaces (GUIs) in conjunction with the expert systems structured are developed and assembled together for standalone installation. These GUIs allow the engineer to edit and input data, produce results numerically and graphically, compare results with a commercial numerical simulator, and generate an interactive 3-D visualization of the multilateral well.

It is expected that the developed integrated artificial expert systems will immensely reduce expenses and time requirements and effectively enhance the overall decision-making process. However, it is worth noting that the proposed expert systems are not to replace the conventional and well established procedures and protocols but rather serve as auxiliary, pre-screening or complementary applications, where and when applicable, to relief some of the computational overhead, provide educated estimation of key reservoir properties or the very least help fine tune them and present the inverse-looking solution to the multi-lateral well design problem or the least a starting point.

Chapter 4 Methodology

This chapter summarizes the procedure and the thinking process applied arriving at the integrated artificial expert systems in the area of forecasting, reservoir evaluation and multilateral well design.

4.1 Feasibility Study

At the very beginning, as a proof of concept, a solution for a proto type of the problem on a smaller scale is developed. The results and lessons learned from this study led to the development of the proposed methodology outlined below and were instrumental to the final development of the integrated expert systems. The details of this study are presented in the following chapter.

4.2 Data Base Generation

This section will highlight the sources and codes used for generating the data base required for assembling the input and output parameters that were necessary for training the artificial neural networks. In general the data used in performing this work is of a synthetic nature; however careful attention was made to reflect reality, physical properties and common sense. All codes used are presented in appendix A.

4.2.1 Reservoir Properties and Well Parameters

A variety of rock and fluid properties spanning tight to conventional sands were generated using a pseudorandom **(randn)** command in **MATLAB**[1] that draws values from a standard normal distribution. The minimum and maximum values for each property were

[1]MATLAB: MATrix LABoratory, a numerical computation, visualization and programming software. A registered trademark of The MathWorks, Inc.

predefined as well as the number of data sets desired, then the command is activated to populate the data sets with pseudorandom values including the minimum and maximum values for each property. The same procedure is applied for producing different multilateral well design configuration parameters covering dual to five laterals and.

4.2.2 Reservoir Geometry and Well Placement

The reservoir geometry used throughout this study is of a regular cubic shape contained in a 31-by-31-by-10 grid system. The wellhead and vertical hole are always in the areal center of the reservoir and the laterals always branch out from the vertical hole. The dimensions and parameters defining the reservoir and the multilateral well for each scenario are obtained from the process explained in the previous section.

4.2.3 Reservoir Performance

A commercial numerical reservoir simulator by Computer Modeling Group **(CMG[1] IMEX[2])** was used for simulating the reservoir performance. A simulation run is performed for each and every scenario presented in the data sets. Given the nature of the study requiring many cases an interface with the simulator was used to efficiently and automatically load and run the desired number of scenarios. The following sections summarize the process.

4.2.3.1 Reservoir Simulator Interface

A **MATLAB®** code that interfaces with the numerical simulator (**CMG® IMEX™**) was developed. This was vital to the efficiency in generating the required data base and later on for developing the Graphical User Interfaces (GUIs) as described later on in this dissertation. The interface simplified the preparation for numerous simulation runs otherwise

[1]CMG: Computer Modelling Group, a registered trademark of Computer Modelling Group Ltd.
[2]IMEX: IMplicit-EXplicit Black Oil Simulator, a registered trademark of Computer Modelling Group Ltd.

would take many hours and days if performed manually. When the interface code is activated it generates a batch file and loads the data sets containing the variable reservoir properties and the corresponding well parameters in a form of a matrix. It then extracts and assigns the reservoir properties, dimensions and well parameters from the loaded data file using an indexing system. This process continues in a do-loop depending on the number of data sets presented. At the end of each loop a ***.dat*** file is created. Up to this point the process takes seconds for a reasonably large data set. For running the simulator **(CMG® IMEX™)** the batch file is activated and the scenarios are automatically run in sequence then the results are stored in the ***.out*** files generated by the simulator. The time required for completing this process is dependent on many factors such as the computer processing power, traffic of users on the simulator server and the number of scenarios.

4.2.3.2 Data Extraction

A number of codes were developed to extract and tabulate specific data from the numerical simulator output files, such as original oil and gas in place, cumulative production and rate decline data. **Figure 4.1** shows the data base generation overall process.

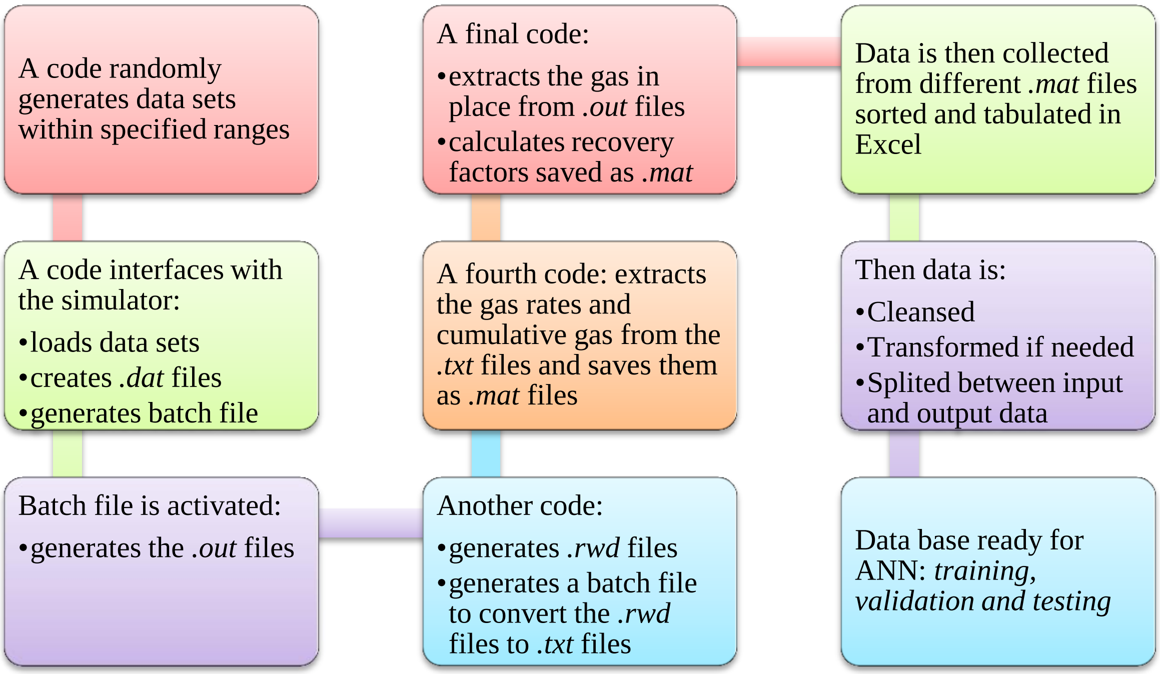


Fig. 4.1: Data Base Preparation Flow Chart.

4.3 Artificial Neural Network Design Workflow

This section summarizes the workflow implemented for designing the neural networks presented in this research.

4.3.1 Data Preparation

Although data preparation in most cases occurs outside the context of the neural network, similar to collecting and extracting the data, yet it has a great impact on its success. The manner in which the data is presented to the network could either simplify and enhance the training and learning process or complicate it. The most common data preparation techniques involve adding functional links and different data transformations or representations as briefly described in the following sections.

4.3.1.1 Functional Links

Functional links are mathematical relationships between input and/or output parameters used to enhance the performance of the neural network. For example, in this study functional links calculating the permeability geometric average and the normal to lateral permeability ratio were added. The details of functional links used are presented in the following chapters.

4.3.1.2 Data Representation

This technique represents the parameter in a different form by transforming it mathematically or replacing it with an index. This is done to reduce the variation in values between the parameters which simplifies the neural network interpretation of the data, hence improving its overall convergence. For example, the large gap between vertical and horizontal permeability or between early and late time percent recoveries was compressed by taking the logarithmic values of those parameters. Similarly a multiplier of 10% was applied to the reservoir thickness. The lengths of the laterals were replaced with the nearest natural number of cells perforated.

4.3.2 Problem Type

Understanding the type of problem has a profound impact on the efficiency of structuring the ANN hence on the effectiveness of its performance. For example, some training functions would fit best for pattern recognition type of problems; others would best serve function approximation problems. Also taking into consideration the size of the neural network, i.e. the number of neurons in the input, output and hidden layers and the number of weights assigned to those connections could yield using slower training functions over faster ones that declines in efficiency for large networks due to the increase in memory and computational time requirements **(MATLAB®, 2011)**.

4.3.3 Setting Up and Training the Network

Following the previously outlined procedure assisted in narrowing down the options when arranging the multi layered feed forward neural network. That is the different combinations of transfer, training and learning functions to choose from. Nevertheless one of the most important factors affecting the success of the ANN is determining the number of hidden layers and its neurons, which involved a heuristic approach. Also, due to the nature of the problem many examples and scenarios covering a wide range were used for training the network to improve its generalization, robustness and reliability.

Chapter 5 Feasibility Study

This chapter demonstrates, as a proof of concept, the ANN developments for a single phase volumetric gas reservoir sector model depleted with a dual-lateral well. The results and lessons learned were the foundation for expanding towards the development of the integrated expert systems for the volumetric single phase gas reservoirs case and multiphase reservoirs with bottom water drive systems case describe in Chapter 6.

5.1 Preliminary Case Description

The subject is a volumetric single phase gas reservoir contained in a closed system of 31-by-31-by-10 grid system. The reservoir is depleted via a dual-lateral with its wellhead and vertical hole centered in the 2D plane of the reservoir. **Figures 5.1** and **5.2** illustrate the simple schematics of the model and **Table 5.1** describes the parameters and their corresponding ranges.

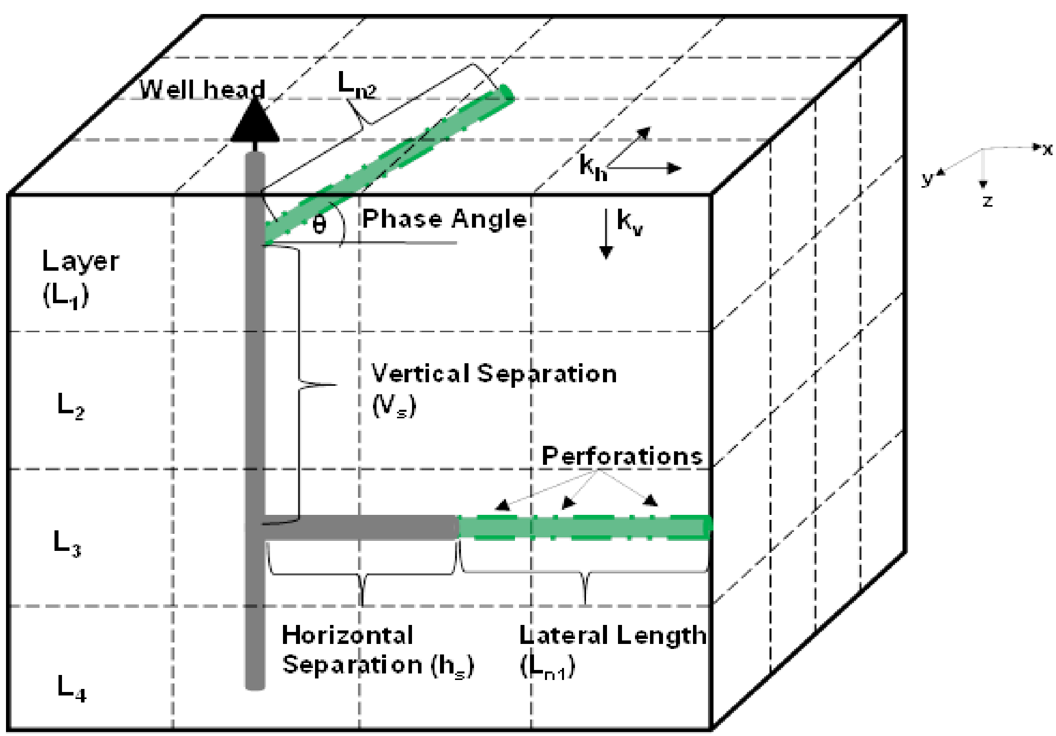


Fig. 5.1: 3D Model Schematics.

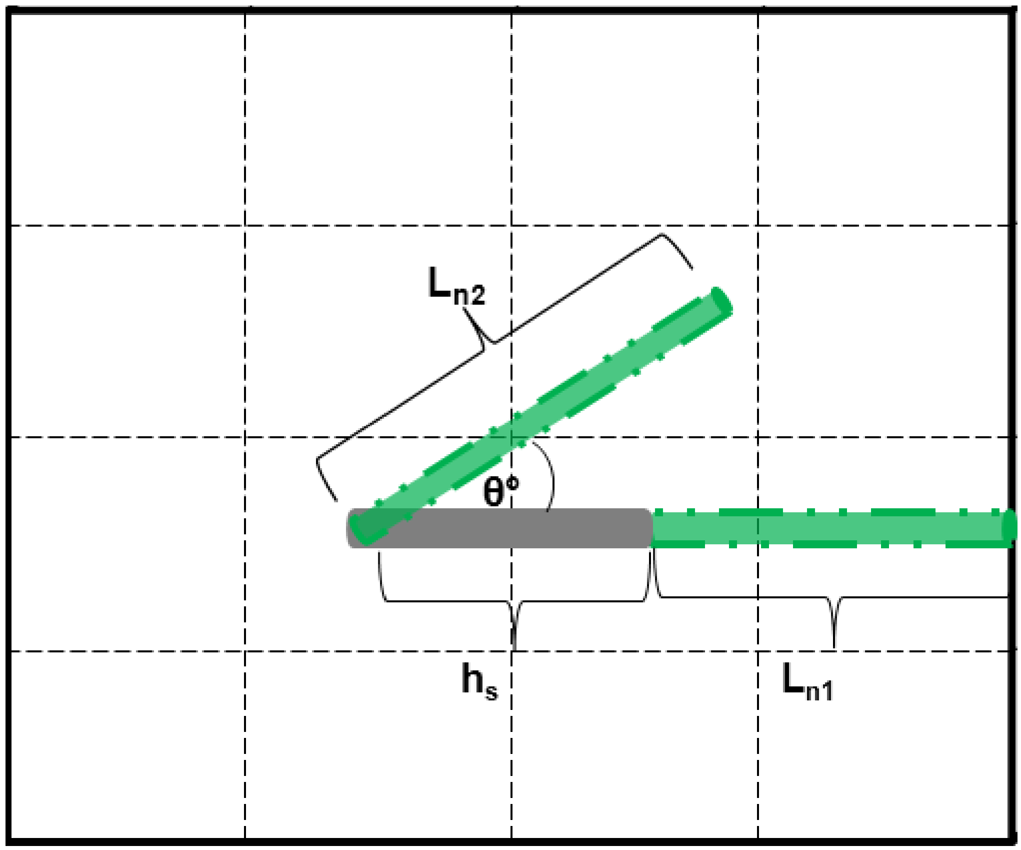


Fig. 5.2: Top View of the Model.

Table 5.1: Parameters and their ranges

Category	Parameter	Abbreviation/Symbol	Units	Minimum	Maximum
Reservoir	Vertical Permeability	k_v	md	0.001	0.01
Reservoir	Horizontal Permeability	k_h	md	0.01	0.1
Functional link	Permeability Ratio	k_v/k_h	ratio	0.1	1.0
Well	Location of 1st lateral	L_1	layer #	1	10
Well	Location of 2nd lateral	L_2	layer #	1	10
Well	Length of 1st lateral	L_{n1}	ft	450	1800
Well	Length of 2nd lateral	L_{n2}	ft	450	1800
Well	Horizontal separation between heels	H_s	ft	0	900
Well	Phase angle between laterals	θ	degrees	45	180

5.2 Approach

For this preliminary case study the method can be divided into two main layers. The first layer is for generating the data base. This layer consist of three sub layers, one is for identifying the parameters and their ranges as shown in **Table 5.1** of the previous section. The second is to randomly generate an adequate number of data sets that represents the population between the parameters ranges. Then these data sets and other predefined reservoir properties and operating conditions are combined to create many reservoir models which are fed to the numerical simulator to generate the recovery profiles for each scenario. The established data base now is the source for allocating the input and output parameters for developing the Forward and Inverse-looking ANN solutions in the second layer. A simple flow chart summarizing the process is illustrated in **Figure 5.3**. The details of the preliminary case study are presented in the following sections. However before going any further what is meant by forward and inverse-looking solutions? These two terms simply reflect the type of problem addressed and what the known and unknowns are. For example, given the distance and the velocity of three different transportation vehicles say, a car, an airplane and a train it is straight forward to solve for the time it took each vehicle to travel the given distance, hence forward-looking. Whereas if given the distance and travel time it is inferably to solve for the type of transportation used, whether it was a car, an airplane or a train, hence inverse-looking.

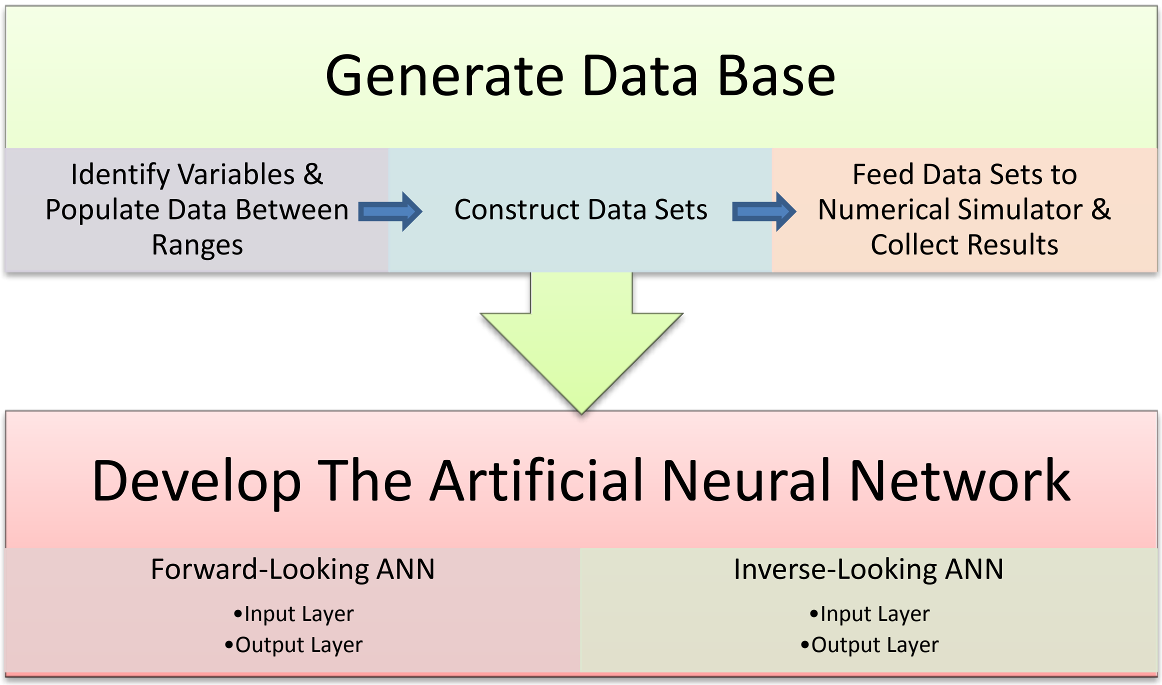


Fig. 5.3: Preliminary Case Study Flow Chart.

5.3 Data Base Generation

A pseudorandom code was used to generate 100 cases for different combinations of reservoir properties and well parameters between the minimum and maximum values mentioned in **Table 5.1** as shown in **Table 5.2**. At this stage the remaining reservoir properties and operating conditions were set constant. These constant parameters presented in **Table 5.3** along with the contents of **Table 5.2** were combined to build the 100 scenarios introduced to the numerical simulator. After running these models by the simulator the cumulative recovery factors at 18 different time steps over a span of ~50 years were collected. With this process we have concluded the data base required for developing the ANNs.

Table 5.2: Pseudorandom Parameters

Case #	k_v	k_h	k_v/k_h	L_1	L_2	L_{n1}	L_{n2}	H_s	θ
1	0.0084	0.0870	0.0960	1	5	1050	1350	150	180
2	0.0027	0.0704	0.0384	6	6	1050	900	150	90
3	0.0021	0.0571	0.0370	9	2	1650	1800	450	45
4	0.0084	0.0369	0.2274	4	7	1050	600	300	90
5	0.0067	0.0734	0.0919	8	9	600	750	150	180
6	0.0011	0.0443	0.0258	6	2	750	1500	0	180
7	0.0091	0.0611	0.1484	8	5	1350	600	300	90
8	0.0056	0.0899	0.0627	8	4	1650	1200	300	90
9	0.0059	0.0859	0.0687	1	10	1800	1500	0	45
10	0.0065	0.0909	0.0711	4	6	750	1500	0	45
11	0.0078	0.0945	0.0830	7	3	1500	600	450	135
12	0.0087	0.0834	0.1043	5	2	1200	1050	150	45
13	0.0044	0.0101	0.4392	10	6	1050	900	0	45
14	0.0018	0.0103	0.1714	8	8	1200	1050	0	90
15	0.0076	0.0179	0.4255	6	9	1050	1200	0	135
16	0.0040	0.0335	0.1192	4	9	1350	600	450	45
17	0.0086	0.0121	0.7101	3	3	1500	1650	150	135
18	0.0043	0.0482	0.0902	9	6	900	1350	300	45
19	0.0085	0.0407	0.2077	5	9	600	600	150	45
20	0.0026	0.0587	0.0441	8	2	1500	1200	0	90
21	0.0022	0.0934	0.0232	2	9	1050	1650	450	135
22	0.0089	0.0369	0.2419	9	9	1500	1500	150	45
23	0.0014	0.0404	0.0345	1	3	750	1350	150	45
24	0.0072	0.0874	0.0822	9	2	600	1050	300	180
25	0.0076	0.0406	0.1871	9	5	1650	750	150	90
26	0.0049	0.0224	0.2200	6	9	1650	1200	150	45
27	0.0044	0.0557	0.0793	2	5	1800	750	300	180
28	0.0098	0.0871	0.1127	3	5	1650	900	450	180
29	0.0046	0.0446	0.1030	7	6	450	1650	300	45
30	0.0050	0.0726	0.0683	8	2	1200	1650	150	45
31	0.0024	0.0665	0.0363	1	2	1800	1500	150	135
32	0.0039	0.0505	0.0779	8	9	1200	1650	150	135
33	0.0038	0.0526	0.0727	10	6	1650	750	0	45
34	0.0091	0.0955	0.0948	4	3	600	1200	450	45
35	0.0032	0.0175	0.1840	7	9	1800	1350	300	90
36	0.0038	0.0352	0.1079	4	2	1650	1650	150	90
37	0.0047	0.0502	0.0932	3	5	1200	1350	300	90
38	0.0074	0.0629	0.1172	8	7	1050	1050	0	45

Case #	k_v	k_h	k_v/k_h	L_1	L_2	L_{n1}	L_{n2}	H_s	θ
39	0.0023	0.0890	0.0258	8	4	900	1500	450	135
40	0.0088	0.0522	0.1693	4	5	1350	1500	150	180
41	0.0017	0.0494	0.0354	6	6	450	1200	300	135
42	0.0052	0.0772	0.0668	5	9	900	600	300	45
43	0.0013	0.0521	0.0244	2	8	1650	1650	300	45
44	0.0078	0.0875	0.0889	1	2	1200	450	150	45
45	0.0073	0.0520	0.1404	5	4	1050	1200	0	90
46	0.0029	0.0548	0.0534	4	4	1050	600	150	90
47	0.0071	0.0539	0.1322	4	9	900	900	0	45
48	0.0060	0.0307	0.1963	4	5	1800	1500	300	135
49	0.0087	0.0177	0.4891	3	3	1800	750	0	135
50	0.0060	0.0161	0.3752	5	6	1200	1650	450	135
51	0.0091	0.0900	0.1013	7	5	1800	1350	300	45
52	0.0048	0.0310	0.1541	3	9	1050	900	450	45
53	0.0042	0.0875	0.0482	7	9	1050	750	300	135
54	0.0054	0.0741	0.0729	5	8	750	750	150	180
55	0.0033	0.0886	0.0373	5	7	750	1500	150	45
56	0.0094	0.0944	0.0992	3	8	1500	450	300	45
57	0.0052	0.0226	0.2304	3	9	1500	1350	450	180
58	0.0033	0.0455	0.0723	7	2	1200	1350	150	90
59	0.0049	0.0983	0.0497	3	4	1500	1500	300	135
60	0.0073	0.0680	0.1076	6	1	1200	1800	0	135
61	0.0046	0.0907	0.0510	10	8	1200	900	300	45
62	0.0026	0.0534	0.0494	7	6	750	750	150	45
63	0.0087	0.0113	0.7726	7	4	1200	1650	300	45
64	0.0063	0.0661	0.0947	10	3	600	1500	150	90
65	0.0044	0.0308	0.1416	8	6	450	1050	0	135
66	0.0030	0.0575	0.0521	6	4	1350	600	150	90
67	0.0030	0.0752	0.0395	10	2	1200	1200	300	45
68	0.0057	0.0647	0.0881	2	2	750	750	0	180
69	0.0049	0.0630	0.0778	3	2	1050	1200	150	90
70	0.0077	0.0490	0.1565	10	5	1350	900	300	45
71	0.0016	0.0320	0.0511	8	2	1200	900	300	45
72	0.0086	0.0486	0.1775	5	5	600	1500	150	90
73	0.0071	0.0109	0.6522	7	9	750	1200	150	90
74	0.0022	0.0648	0.0344	5	4	450	1500	450	135
75	0.0087	0.0962	0.0907	4	2	1050	750	300	45
76	0.0028	0.0186	0.1505	3	6	1050	1350	150	45
77	0.0065	0.0132	0.4897	4	9	600	450	300	45
78	0.0059	0.0898	0.0656	1	4	1350	1500	150	135

Case #	k_v	k_h	k_v/k_h	L_1	L_2	L_{n1}	L_{n2}	H_s	θ
79	0.0025	0.0322	0.0764	5	1	450	1350	150	45
80	0.0011	0.0108	0.0973	4	2	600	1800	0	45
81	0.0079	0.0833	0.0953	10	2	1800	600	150	45
82	0.0079	0.0226	0.3481	6	8	1800	1650	150	135
83	0.0048	0.0892	0.0537	9	5	450	1200	150	90
84	0.0015	0.0186	0.0813	5	7	1050	1350	150	90
85	0.0063	0.0417	0.1503	5	7	1650	900	150	135
86	0.0026	0.0634	0.0405	8	6	750	600	450	135
87	0.0076	0.0627	0.1206	10	7	1650	1650	450	135
88	0.0058	0.0701	0.0829	6	9	1500	600	150	45
89	0.0033	0.0683	0.0480	9	7	1350	900	150	90
90	0.0093	0.0490	0.1888	8	9	450	1350	300	180
91	0.0078	0.0226	0.3465	6	5	900	1800	150	90
92	0.0090	0.0777	0.1157	10	2	1650	1200	150	135
93	0.0016	0.0318	0.0510	8	2	1350	1800	450	180
94	0.0027	0.0685	0.0387	10	7	900	750	150	135
95	0.0076	0.0872	0.0876	7	4	1350	1050	450	45
96	0.0073	0.0176	0.4132	4	7	750	1350	0	45
97	0.0080	0.0975	0.0820	5	7	1200	600	150	90
98	0.0055	0.0128	0.4300	9	6	1800	1500	300	45
99	0.0048	0.0852	0.0567	1	7	1650	1050	300	90
100	0.0065	0.0852	0.0763	2	6	900	1500	150	180

Table 5.3: Constant Reservoir Properties and Operating Parameters

Category	Parameter	Abbreviation/Symbol	Units	Value
Reservoir	Drainage Area	D_A	Acres	~500
Reservoir	Total Thickness	H	ft	200
Reservoir	Porosity	Φ	fraction	0.2
Reservoir	Temperature	TRES	°F	150
Reservoir	Initial Pressure	Pi	psi	3500
Reservoir	Gas Density	ρ_g	lb/ft^3	0.066
Operating Condition	Minimum Flowing Bottom Hole Pressure	P_{wf}	psi	500
Operating Condition	Minimum Gas Rate	Q_g	Mscf/d	500

5.4 Forward-Looking ANN

This section will demonstrate the development of the Forward-looking ANN solution for the preliminary case study. The purpose was to test the feasibility of developing a forecasting expert system for reservoirs with a multilateral well that will serve as a proxy to the numerical simulator and as a cross check mechanism in the absence of the numerical simulator later on in this dissertation. The development gradually expands the base of the input layer, meaning that the number of input parameters was gradually increased to include reservoir properties that were previously set constant whereas the multilateral configurations were limited to a dual-lateral only. Even though one of the main advantages of having an expert system is to know more with less, however the end in mind here is to achieve a system with an acceptable generalization of the problem that can distinguish the reservoir performance of many different combinations of multilateral and reservoir properties.

5.4.1 Initial Forward-Looking ANN Solution

For the initial development the contents of **Table 5.2** and the cumulative recovery factors produced by the numerical simulator shown in **Table 5.4** were the input and output data respectively for constructing the ANN. Hence 100 cases with 9 parameters each, represented the input layer, and a corresponding 100 cases with 18 cumulative recovery factors each, represented the output layer. For building the network, it was elected to use the hyperbolic tangent sigmoid **'tansig'** and the linear **'purelin'** as the transfer functions, the conjugate gradient backpropagation with Polak- Ribiére updates **'traincgp'** as the training function, the gradient descent with momentum weighted and bias learning function **'learngdem'**, and the mean squared error with regularization performance function **'msereg' (MATLAB®, 2011)**.

Table 5.4: Cumulative Recovery Factors Produced by the Numerical Simulator

Time Step	Case# 1	2	3	4	5	6	7	8	9	10
1 d	9.E-05	4.E-05	5.E-05	4.E-05	4.E-05	2.E-05	6.E-05	9.E-05	9.E-05	7.E-05
90 d	0.005	0.002	0.003	0.003	0.003	0.002	0.004	0.006	0.005	0.004
180 d	0.010	0.004	0.006	0.005	0.005	0.003	0.008	0.010	0.009	0.008
270 d	0.014	0.006	0.008	0.007	0.007	0.004	0.011	0.015	0.012	0.012
1 yr	0.018	0.008	0.011	0.009	0.009	0.005	0.014	0.019	0.016	0.015
2 yr	0.033	0.015	0.020	0.017	0.017	0.010	0.025	0.036	0.029	0.028
3 yr	0.047	0.022	0.028	0.024	0.024	0.015	0.036	0.051	0.042	0.040
4 yr	0.061	0.029	0.036	0.031	0.031	0.019	0.046	0.066	0.053	0.051
5 yr	0.073	0.036	0.044	0.037	0.038	0.023	0.056	0.079	0.065	0.062
6 yr	0.086	0.042	0.051	0.043	0.045	0.027	0.065	0.092	0.075	0.072
7 yr	0.098	0.048	0.059	0.049	0.052	0.032	0.074	0.105	0.086	0.082
14 yr	0.172	0.089	0.104	0.088	0.096	0.059	0.131	0.184	0.152	0.147
21 yr	0.236	0.127	0.144	0.122	0.135	0.084	0.180	0.249	0.208	0.202
28 yr	0.291	0.162	0.180	0.153	0.172	0.108	0.224	0.305	0.258	0.251
35 yr	0.340	0.194	0.213	0.183	0.206	0.131	0.264	0.354	0.302	0.295
42 yr	0.383	0.224	0.243	0.210	0.237	0.153	0.300	0.397	0.341	0.334
49 yr	0.421	0.252	0.271	0.235	0.267	0.174	0.332	0.435	0.377	0.370
50 yr	0.424	0.255	0.273	0.238	0.269	0.176	0.335	0.438	0.380	0.373

*d = day, yr = year

Cont. Table 5.4

Time Step	Case# 11	12	13	14	15	16	17	18	19	20
1 d	7.E-05	7.E-05	2.E-05	1.E-05	3.E-05	3.E-05	4.E-05	4.E-05	3.E-05	5.E-05
90 d	0.005	0.004	0.001	0.001	0.002	0.002	0.003	0.003	0.002	0.003
180 d	0.009	0.008	0.002	0.002	0.004	0.003	0.005	0.005	0.003	0.006
270 d	0.013	0.012	0.003	0.003	0.006	0.005	0.007	0.007	0.005	0.008
1 yr	0.016	0.015	0.004	0.003	0.007	0.006	0.009	0.009	0.006	0.010
2 yr	0.031	0.027	0.007	0.006	0.013	0.011	0.016	0.016	0.011	0.020
3 yr	0.044	0.039	0.009	0.008	0.019	0.015	0.022	0.023	0.015	0.028
4 yr	0.057	0.049	0.012	0.011	0.024	0.020	0.028	0.030	0.019	0.036
5 yr	0.069	0.060	0.014	0.013	0.029	0.024	0.034	0.036	0.024	0.044
6 yr	0.081	0.070	0.017	0.015	0.033	0.028	0.039	0.042	0.028	0.051
7 yr	0.092	0.079	0.019	0.018	0.038	0.032	0.044	0.048	0.032	0.059
14 yr	0.165	0.140	0.032	0.032	0.065	0.058	0.076	0.086	0.058	0.106
21 yr	0.226	0.193	0.045	0.044	0.090	0.082	0.104	0.121	0.082	0.148
28 yr	0.279	0.240	0.056	0.056	0.112	0.105	0.129	0.152	0.105	0.187
35 yr	0.327	0.282	0.067	0.068	0.133	0.126	0.152	0.181	0.127	0.222
42 yr	0.368	0.320	0.077	0.079	0.153	0.146	0.174	0.209	0.147	0.255
49 yr	0.406	0.355	0.087	0.089	0.172	0.165	0.194	0.234	0.167	0.285
50 yr	0.409	0.358	0.088	0.090	0.174	0.167	0.196	0.237	0.169	0.288

Cont. Table 5.4

Time Step	Case# 21	22	23	24	25	26	27	28	29	30
1 d	5.E-05	6.E-05	2.E-05	6.E-05	6.E-05	4.E-05	6.E-05	1.E-04	4.E-05	7.E-05
90 d	0.003	0.004	0.001	0.003	0.004	0.002	0.004	0.006	0.003	0.004
180 d	0.006	0.007	0.003	0.006	0.007	0.005	0.007	0.012	0.005	0.008
270 d	0.008	0.010	0.004	0.009	0.010	0.006	0.009	0.017	0.007	0.011
1 yr	0.011	0.013	0.005	0.012	0.012	0.008	0.012	0.022	0.009	0.015
2 yr	0.020	0.022	0.009	0.023	0.023	0.015	0.023	0.040	0.016	0.027
3 yr	0.029	0.031	0.013	0.032	0.032	0.021	0.032	0.057	0.023	0.038
4 yr	0.038	0.040	0.016	0.042	0.041	0.027	0.042	0.073	0.030	0.048
5 yr	0.047	0.047	0.020	0.051	0.049	0.032	0.051	0.089	0.036	0.058
6 yr	0.055	0.055	0.023	0.060	0.057	0.037	0.060	0.103	0.042	0.068
7 yr	0.064	0.062	0.027	0.069	0.065	0.042	0.068	0.117	0.048	0.077
14 yr	0.118	0.106	0.050	0.126	0.113	0.074	0.122	0.204	0.085	0.137
21 yr	0.166	0.145	0.071	0.177	0.155	0.101	0.170	0.276	0.119	0.188
28 yr	0.209	0.180	0.092	0.222	0.193	0.126	0.213	0.336	0.149	0.233
35 yr	0.249	0.211	0.111	0.263	0.227	0.149	0.251	0.388	0.178	0.274
42 yr	0.285	0.240	0.130	0.301	0.259	0.171	0.287	0.433	0.204	0.310
49 yr	0.318	0.267	0.148	0.335	0.288	0.191	0.319	0.473	0.229	0.344
50 yr	0.321	0.269	0.149	0.338	0.290	0.193	0.322	0.477	0.231	0.347

Cont. Table 5.4

Time Step	Case# 31	32	33	34	35	36	37	38	39	40
1 d	5.E-05	5.E-05	4.E-05	7.E-05	3.E-05	5.E-05	6.E-05	5.E-05	4.E-05	9.E-05
90 d	0.003	0.003	0.002	0.004	0.002	0.004	0.004	0.003	0.003	0.005
180 d	0.006	0.006	0.005	0.007	0.004	0.007	0.007	0.006	0.005	0.010
270 d	0.008	0.008	0.007	0.010	0.006	0.009	0.010	0.009	0.007	0.015
1 yr	0.011	0.011	0.008	0.013	0.008	0.012	0.012	0.011	0.010	0.019
2 yr	0.020	0.021	0.016	0.025	0.015	0.022	0.023	0.021	0.018	0.034
3 yr	0.029	0.030	0.022	0.035	0.021	0.031	0.033	0.029	0.027	0.048
4 yr	0.037	0.038	0.029	0.045	0.027	0.040	0.042	0.037	0.035	0.061
5 yr	0.045	0.046	0.035	0.055	0.032	0.048	0.051	0.045	0.043	0.073
6 yr	0.053	0.055	0.041	0.064	0.038	0.056	0.060	0.053	0.051	0.085
7 yr	0.061	0.062	0.047	0.073	0.043	0.064	0.068	0.060	0.059	0.097
14 yr	0.112	0.113	0.086	0.130	0.076	0.113	0.121	0.108	0.110	0.167
21 yr	0.158	0.158	0.121	0.180	0.105	0.155	0.168	0.150	0.155	0.227
28 yr	0.199	0.199	0.153	0.224	0.131	0.193	0.209	0.189	0.197	0.279
35 yr	0.237	0.236	0.183	0.264	0.155	0.227	0.246	0.224	0.235	0.325
42 yr	0.271	0.270	0.211	0.301	0.177	0.259	0.281	0.257	0.269	0.366
49 yr	0.303	0.301	0.237	0.334	0.198	0.288	0.312	0.287	0.302	0.402
50 yr	0.306	0.304	0.240	0.337	0.200	0.291	0.315	0.290	0.305	0.406

Cont. Table 5.4

Time Step	Case# 41	42	43	44	45	46	47	48	49	50
1 d	2.E-05	3.E-05	3.E-05	5.E-05	6.E-05	3.E-05	4.E-05	6.E-05	4.E-05	3.E-05
90 d	0.001	0.002	0.002	0.003	0.004	0.002	0.003	0.004	0.003	0.002
180 d	0.002	0.004	0.004	0.005	0.007	0.003	0.005	0.007	0.005	0.004
270 d	0.003	0.006	0.006	0.007	0.010	0.005	0.007	0.010	0.007	0.006
1 yr	0.004	0.008	0.008	0.009	0.013	0.006	0.009	0.013	0.009	0.008
2 yr	0.008	0.014	0.015	0.017	0.024	0.012	0.016	0.024	0.016	0.015
3 yr	0.012	0.020	0.022	0.024	0.033	0.017	0.023	0.034	0.022	0.022
4 yr	0.015	0.026	0.028	0.032	0.042	0.022	0.029	0.043	0.028	0.028
5 yr	0.019	0.032	0.034	0.039	0.051	0.027	0.035	0.053	0.034	0.034
6 yr	0.022	0.038	0.040	0.045	0.059	0.032	0.041	0.061	0.039	0.040
7 yr	0.026	0.044	0.046	0.052	0.067	0.037	0.047	0.070	0.044	0.045
14 yr	0.049	0.081	0.084	0.096	0.118	0.069	0.086	0.123	0.076	0.081
21 yr	0.071	0.116	0.118	0.136	0.164	0.099	0.120	0.168	0.104	0.112
28 yr	0.093	0.148	0.149	0.173	0.204	0.126	0.153	0.209	0.129	0.140
35 yr	0.113	0.178	0.178	0.207	0.241	0.152	0.183	0.245	0.152	0.166
42 yr	0.132	0.206	0.205	0.238	0.275	0.177	0.211	0.279	0.174	0.190
49 yr	0.151	0.232	0.231	0.267	0.306	0.200	0.237	0.310	0.194	0.213
50 yr	0.153	0.235	0.233	0.270	0.309	0.203	0.240	0.312	0.196	0.215

Cont. Table 5.4

Time Step	Case# 51	52	53	54	55	56	57	58	59	60
1 d	1.E-04	3.E-05	4.E-05	4.E-05	5.E-05	6.E-05	4.E-05	4.E-05	8.E-05	8.E-05
90 d	0.006	0.002	0.003	0.003	0.003	0.004	0.003	0.003	0.005	0.005
180 d	0.012	0.004	0.005	0.005	0.006	0.007	0.005	0.005	0.009	0.008
270 d	0.017	0.005	0.008	0.007	0.009	0.011	0.008	0.008	0.014	0.012
1 yr	0.022	0.006	0.010	0.010	0.011	0.014	0.010	0.010	0.018	0.016
2 yr	0.039	0.012	0.020	0.018	0.021	0.026	0.018	0.018	0.034	0.029
3 yr	0.055	0.017	0.028	0.026	0.030	0.037	0.025	0.026	0.048	0.041
4 yr	0.069	0.021	0.037	0.033	0.039	0.047	0.032	0.034	0.062	0.052
5 yr	0.083	0.026	0.045	0.041	0.048	0.057	0.039	0.041	0.076	0.064
6 yr	0.096	0.030	0.054	0.048	0.056	0.067	0.046	0.048	0.089	0.074
7 yr	0.108	0.034	0.062	0.055	0.064	0.076	0.052	0.054	0.102	0.085
14 yr	0.185	0.061	0.114	0.101	0.117	0.137	0.093	0.098	0.181	0.150
21 yr	0.248	0.085	0.161	0.143	0.164	0.189	0.129	0.137	0.249	0.207
28 yr	0.302	0.108	0.203	0.182	0.206	0.235	0.161	0.172	0.306	0.256
35 yr	0.348	0.129	0.242	0.217	0.244	0.277	0.191	0.205	0.357	0.301
42 yr	0.389	0.150	0.277	0.250	0.279	0.315	0.219	0.235	0.401	0.340
49 yr	0.426	0.169	0.310	0.280	0.311	0.349	0.245	0.264	0.440	0.376
50 yr	0.429	0.171	0.313	0.283	0.314	0.352	0.248	0.266	0.443	0.380

Cont. Table 5.4

Time Step	Case# 61	62	63	64	65	66	67	68	69	70
1 d	5.E-05	2.E-05	4.E-05	6.E-05	2.E-05	4.E-05	4.E-05	4.E-05	6.E-05	5.E-05
90 d	0.003	0.001	0.003	0.004	0.001	0.002	0.003	0.002	0.003	0.003
180 d	0.006	0.003	0.005	0.007	0.003	0.004	0.005	0.004	0.006	0.006
270 d	0.008	0.004	0.007	0.010	0.004	0.006	0.007	0.006	0.009	0.008
1 yr	0.010	0.005	0.008	0.012	0.005	0.008	0.010	0.007	0.012	0.010
2 yr	0.019	0.010	0.015	0.023	0.009	0.016	0.018	0.014	0.022	0.018
3 yr	0.028	0.014	0.021	0.033	0.013	0.023	0.026	0.020	0.031	0.026
4 yr	0.036	0.018	0.026	0.042	0.016	0.029	0.033	0.026	0.040	0.033
5 yr	0.043	0.022	0.030	0.051	0.020	0.036	0.040	0.032	0.048	0.040
6 yr	0.051	0.026	0.035	0.059	0.023	0.042	0.047	0.037	0.056	0.047
7 yr	0.058	0.030	0.039	0.068	0.027	0.048	0.054	0.043	0.064	0.053
14 yr	0.107	0.057	0.064	0.121	0.049	0.088	0.099	0.080	0.115	0.094
21 yr	0.150	0.081	0.085	0.168	0.070	0.125	0.139	0.113	0.161	0.131
28 yr	0.189	0.105	0.104	0.210	0.090	0.159	0.176	0.145	0.202	0.164
35 yr	0.225	0.127	0.121	0.248	0.109	0.190	0.209	0.174	0.239	0.195
42 yr	0.258	0.148	0.137	0.283	0.127	0.219	0.241	0.202	0.273	0.224
49 yr	0.289	0.169	0.152	0.314	0.145	0.246	0.270	0.228	0.305	0.251
50 yr	0.291	0.171	0.153	0.317	0.146	0.249	0.272	0.230	0.308	0.253

Cont. Table 5.4

Time Step	Case# 71	72	73	74	75	76	77	78	79	80
1 d	2.E-05	6.E-05	3.E-05	3.E-05	6.E-05	2.E-05	1.E-05	8.E-05	2.E-05	1.E-05
90 d	0.001	0.004	0.002	0.002	0.004	0.002	0.001	0.005	0.001	0.001
180 d	0.002	0.007	0.003	0.003	0.007	0.003	0.002	0.009	0.002	0.001
270 d	0.003	0.010	0.004	0.005	0.010	0.004	0.002	0.012	0.003	0.002
1 yr	0.005	0.012	0.006	0.006	0.012	0.005	0.003	0.016	0.004	0.003
2 yr	0.008	0.023	0.010	0.012	0.023	0.010	0.005	0.030	0.008	0.005
3 yr	0.012	0.032	0.014	0.018	0.032	0.014	0.007	0.043	0.011	0.007
4 yr	0.016	0.041	0.018	0.024	0.042	0.018	0.009	0.055	0.015	0.009
5 yr	0.019	0.050	0.021	0.029	0.051	0.021	0.011	0.067	0.018	0.011
6 yr	0.023	0.058	0.025	0.035	0.059	0.025	0.012	0.079	0.021	0.013
7 yr	0.026	0.066	0.028	0.040	0.068	0.028	0.014	0.090	0.024	0.015
14 yr	0.048	0.116	0.048	0.076	0.123	0.050	0.025	0.161	0.045	0.027
21 yr	0.069	0.159	0.065	0.108	0.171	0.070	0.035	0.222	0.064	0.038
28 yr	0.088	0.199	0.081	0.138	0.214	0.088	0.045	0.276	0.082	0.049
35 yr	0.107	0.234	0.096	0.167	0.254	0.105	0.054	0.323	0.100	0.059
42 yr	0.125	0.267	0.110	0.194	0.290	0.122	0.064	0.365	0.117	0.069
49 yr	0.142	0.297	0.124	0.219	0.323	0.137	0.072	0.403	0.133	0.078
50 yr	0.143	0.300	0.125	0.221	0.326	0.139	0.073	0.406	0.134	0.079

Cont. Table 5.4

Time Step	Case# 81	82	83	84	85	86	87	88	89	90
1 d	6.E-05	6.E-05	5.E-05	2.E-05	5.E-05	2.E-05	9.E-05	5.E-05	5.E-05	5.E-05
90 d	0.004	0.004	0.003	0.001	0.003	0.001	0.005	0.003	0.003	0.003
180 d	0.007	0.007	0.006	0.002	0.006	0.003	0.010	0.006	0.006	0.006
270 d	0.010	0.010	0.008	0.003	0.009	0.004	0.014	0.008	0.008	0.009
1 yr	0.013	0.013	0.011	0.005	0.012	0.005	0.018	0.011	0.010	0.011
2 yr	0.024	0.024	0.020	0.008	0.022	0.010	0.033	0.019	0.019	0.021
3 yr	0.034	0.034	0.029	0.012	0.031	0.015	0.047	0.028	0.028	0.029
4 yr	0.044	0.043	0.037	0.016	0.040	0.020	0.061	0.036	0.036	0.038
5 yr	0.053	0.052	0.046	0.019	0.048	0.024	0.074	0.044	0.044	0.046
6 yr	0.063	0.060	0.054	0.023	0.056	0.029	0.086	0.051	0.051	0.053
7 yr	0.072	0.068	0.062	0.026	0.064	0.033	0.098	0.058	0.059	0.061
14 yr	0.128	0.118	0.113	0.047	0.114	0.063	0.173	0.106	0.107	0.109
21 yr	0.178	0.160	0.159	0.067	0.157	0.091	0.236	0.148	0.150	0.151
28 yr	0.223	0.197	0.200	0.085	0.196	0.118	0.290	0.187	0.189	0.190
35 yr	0.263	0.231	0.238	0.103	0.231	0.143	0.337	0.222	0.225	0.225
42 yr	0.299	0.262	0.273	0.119	0.264	0.167	0.379	0.255	0.258	0.258
49 yr	0.333	0.291	0.305	0.135	0.294	0.189	0.416	0.285	0.289	0.288
50 yr	0.336	0.293	0.308	0.137	0.297	0.191	0.420	0.288	0.291	0.291

Cont. Table 5.4

Time Step	Case# 91	92	93	94	95	96	97	98	99	100
1 d	5.E-05	9.E-05	3.E-05	3.E-05	7.E-05	3.E-05	7.E-05	3.E-05	8.E-05	8.E-05
90 d	0.003	0.005	0.002	0.002	0.004	0.002	0.004	0.002	0.004	0.005
180 d	0.006	0.010	0.004	0.003	0.008	0.004	0.008	0.004	0.008	0.009
270 d	0.009	0.014	0.006	0.005	0.012	0.006	0.012	0.006	0.012	0.013
1 yr	0.012	0.018	0.008	0.006	0.015	0.007	0.015	0.008	0.015	0.017
2 yr	0.021	0.033	0.014	0.012	0.028	0.013	0.028	0.014	0.028	0.031
3 yr	0.030	0.047	0.020	0.017	0.039	0.018	0.040	0.019	0.040	0.045
4 yr	0.037	0.061	0.026	0.023	0.050	0.022	0.052	0.024	0.052	0.057
5 yr	0.045	0.074	0.032	0.028	0.061	0.027	0.063	0.029	0.063	0.070
6 yr	0.051	0.086	0.037	0.033	0.071	0.031	0.073	0.034	0.074	0.081
7 yr	0.058	0.098	0.043	0.038	0.080	0.035	0.084	0.038	0.084	0.093
14 yr	0.099	0.172	0.079	0.071	0.142	0.060	0.149	0.065	0.151	0.165
21 yr	0.133	0.236	0.111	0.102	0.194	0.081	0.207	0.087	0.208	0.227
28 yr	0.164	0.290	0.141	0.131	0.241	0.102	0.257	0.107	0.258	0.280
35 yr	0.192	0.339	0.170	0.159	0.282	0.120	0.302	0.125	0.302	0.328
42 yr	0.218	0.381	0.196	0.184	0.320	0.138	0.342	0.142	0.342	0.370
49 yr	0.243	0.419	0.221	0.209	0.354	0.155	0.378	0.158	0.378	0.407
50 yr	0.245	0.422	0.224	0.211	0.357	0.157	0.381	0.160	0.381	0.411

A network with an input layer of 9 neurons, an output layer of 18 neurons and with a single hidden layer was set up. To determine the number of neurons contained by the hidden layer that will yield the minimum error, a do loop from 2 to 100 neurons were tested and stored the results for each loop. At the end of training each ANN set up the error between the target or desired output and the predicted output for each network was calculated and the network with the minimum error was selected. One hidden layer with 27 neurons resulted in the lowest average error of 4.44% calculated using equation (5.1) where (RF) stands for recovery factors, which is within acceptable limits for this case study. The accepted ANN architecture is shown in **Figure 5.4** and the corresponding regression plots are presented in **Figure 5.5**. When executing this specific architecture it takes less than 5 seconds to obtain the corresponding recovery factors of 100 combinations of reservoir properties and well configurations, whereas it took around a couple of hours, using the interface code, to run the similar scenarios using the numerical reservoir simulator and it could take a couple of days if run manually.

$$\%\,Error = 100 \times \sum_{i=1}^{n} \frac{|RF_{Target} - RF_{ANN}|}{RF_{Target}}, n = total\ number\ of\ the\ testing\ set \quad (5.1)$$

The overall process continuously divided the data sets randomly so that 70% of the data set is allocated for training, 19% for validation and 11% for testing. The average percentage error being tracked throughout this dissertation is of the testing data set since they are not introduced to the network during the training and validation phase. **Figure 5.6** demonstrates cases 39 and 63 the best and the worst match respectively between the simulator and the ANN recovery profiles predictions. The other 9 scenarios illustrated in **Figure 5.7** show an overall excellent match.

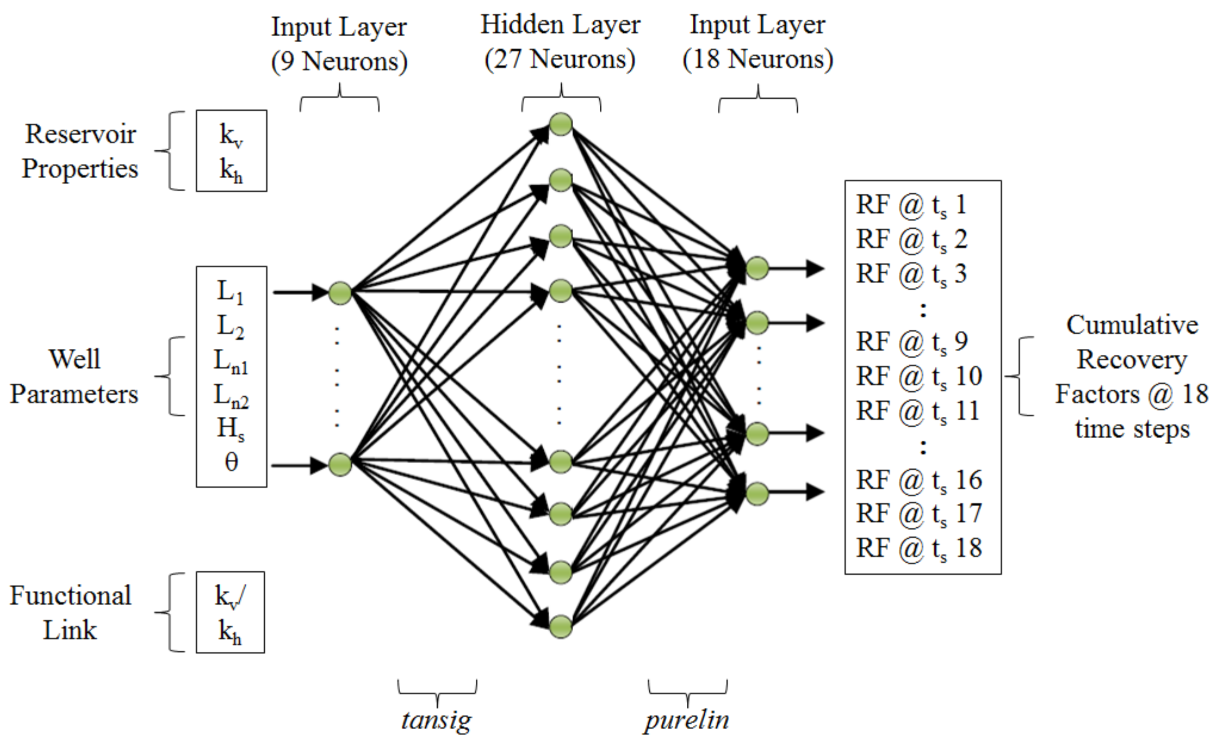


Fig. 5.4: ANN Architecture for the Initial Forward-Looking solution.

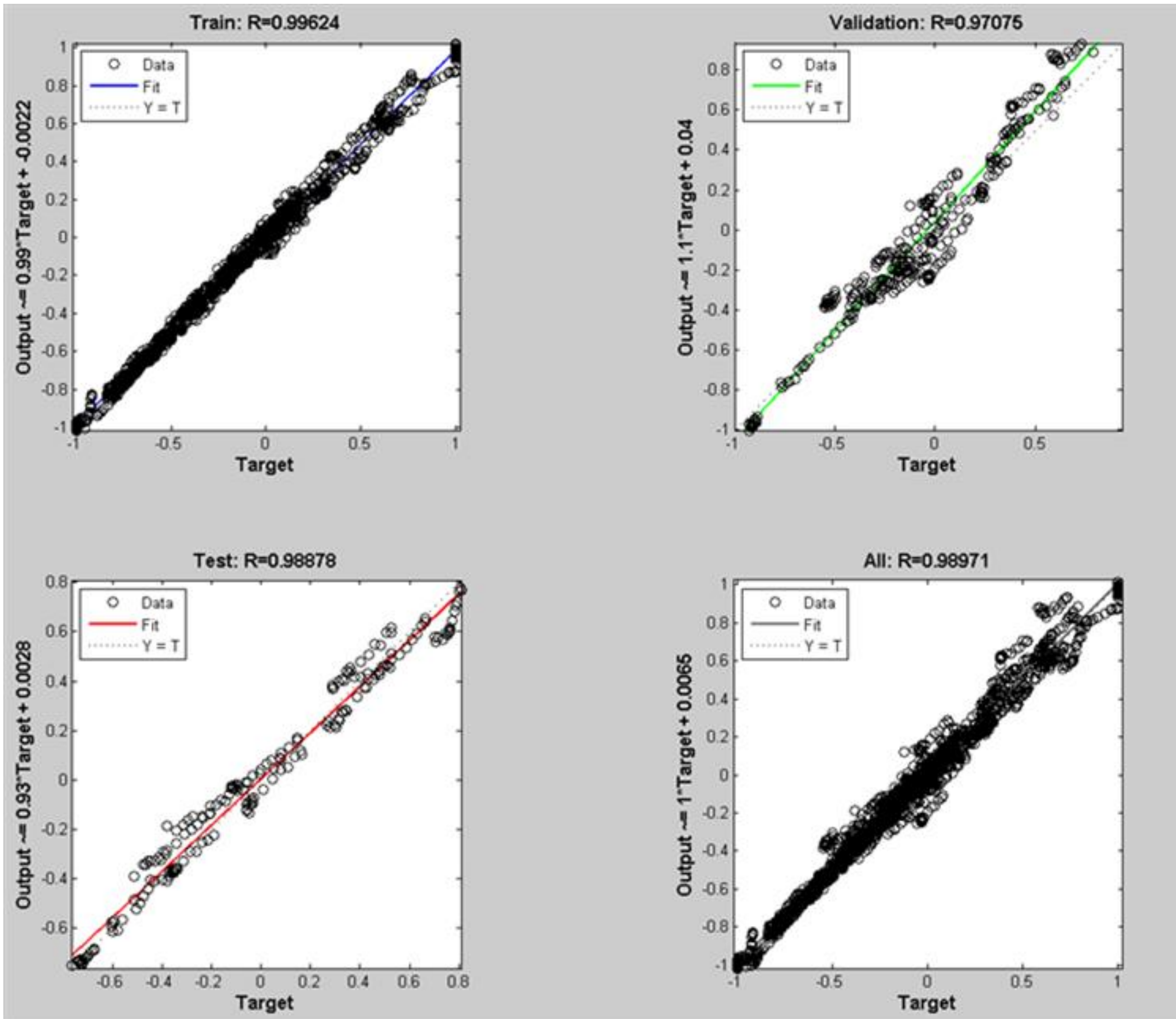
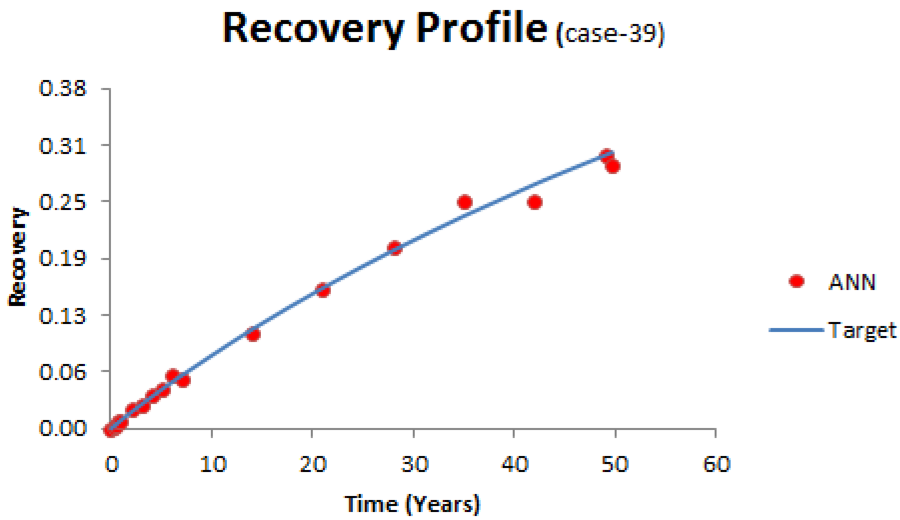


Fig. 5.5: Regression Plots for the Forward-Looking ANN solution of Fig. 5.4.



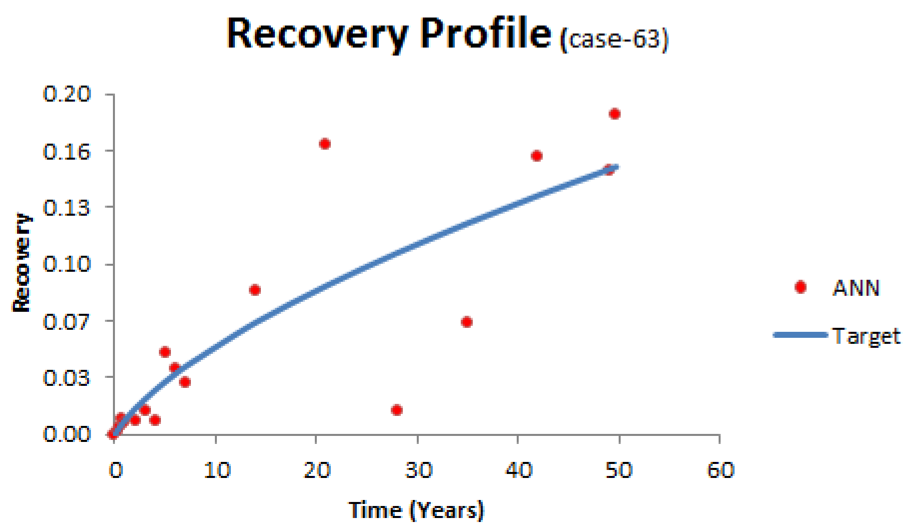


Fig. 5.6: Recovery Profile Predictions, ANN vs. Simulator, (best & worst match).

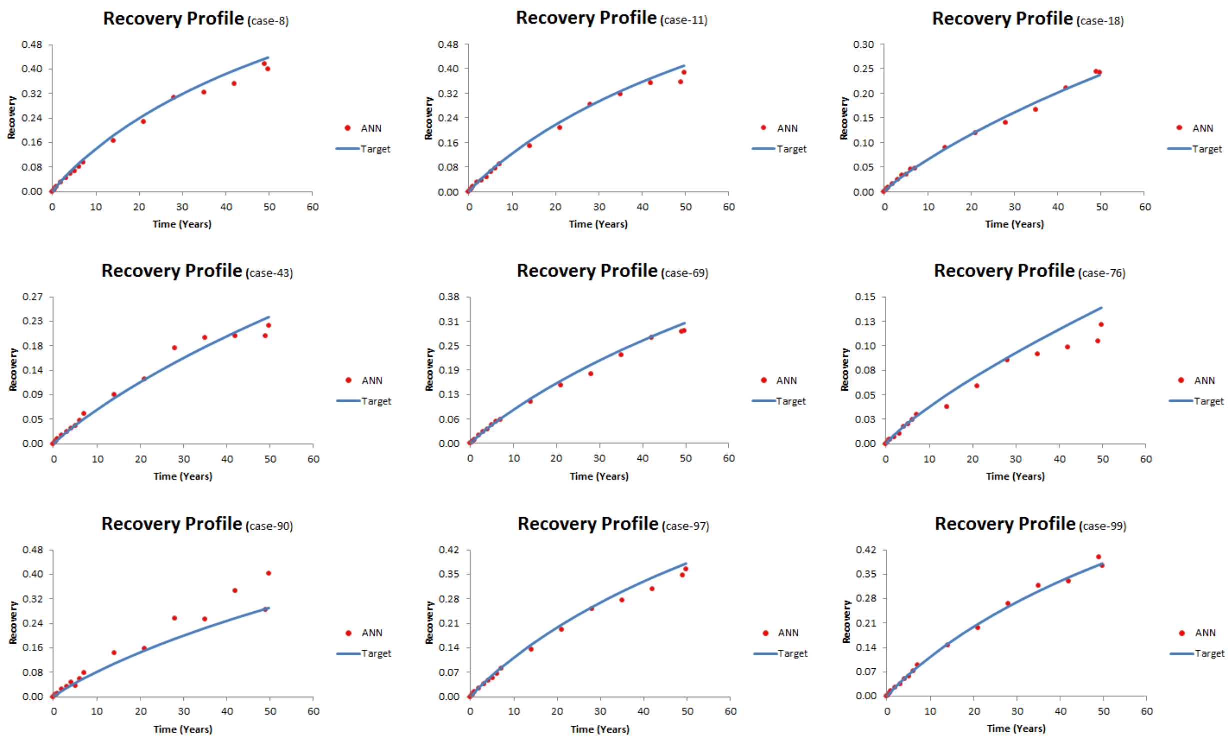


Fig. 5.7: The Remaining Comparison Plots for the Test set.

5.4.2 Expanded Forward-Looking ANN Solution

The expanded Forward-looking ANN featured a total of 17 input parameters representing 8 reservoir properties, 6 well design parameters and 3 functional links as illustrated in **Table 5.5** and the objective remains the same, i.e. predicting the recovery profile at 18 different time steps. As mentioned previously the expansion to this point was done gradually by moving parameters from the constant list of **Table 5.3** to the variables introduced to the input layer of the ANN. At this stage the pool of data has increased to a total of 1656 data sets. Towards achieving a successful network 23 ANNs were tested against the simulator forecasts of 26 new data sets by varying the transfer, training and learning functions also by varying the number of hidden layers and the number of neurons contained in each layer. The successful ANN, network 18, consisted of two hidden layers, 22 and 29 neurons respectively. The log-sigmoid ***'logsig'*** and the linear ***'purelin'*** transfer functions, the bayesian regulation backpropagation as the training function ***'trainbr'***, and the gradient descent with momentum weight and bias as the learning function ***'learngdm'*** **(MATLAB®, 2011)**. The total average error was ~7.9%. **Figure 5.8** illustrates the ANN schematic. Some of the 26 recovery profile comparison plots are shown in **Figure 5.9**.

Table 5.5: Expanded Forward-Looking ANN Input Parameters and their ranges

Category	Parameter	Abbreviation/Symbol	Unit/Rep	Min	Max
Reservoir	Vertical Permeability	k_v	md	0.001	0.01
Reservoir	Lateral Permeability in the ith direction	k_i	md	0.01	0.1
Reservoir	Lateral Permeability in the jth direction	k_j	md	0.01	0.1
Reservoir	Porosity	Φ	fraction	0.05	0.35
Reservoir	Total Reservoir Thickness	H	ft	10	200
Reservoir	Drainage Area	D_A	acres	100	500
Reservoir	Gas Density	ρ_g	lb/ft^3	0.04	0.08
Reservoir	Initial Pressure	P_i	psi	1500	5300
Functional link	Lateral Permeability Geometric Average	k_{geom}	md	0.01	0.1

Cont. Table 5.5

Category	Parameter	Abbreviation/Symbol	Unit/Rep	Min	Max
Functional link	Permeability Ratio	k_v/k_{geom}	ratio	0.01	1.0
Well	Location of 1^{st} lateral	L_1	layer #	1	10
Well	Location of 2^{nd} lateral	L_2	layer #	1	10
Well	Length of 1^{st} lateral	L_{n1}	ft	450	1800
Well	Length of 2^{nd} lateral	L_{n2}	ft	450	1800
Well	Horizontal separation between heels	H_s	ft	0	900
Well	Phase angle between laterals	θ	degrees	45	180
Functional Link	Vertical Separation	V_s	ft	0	160

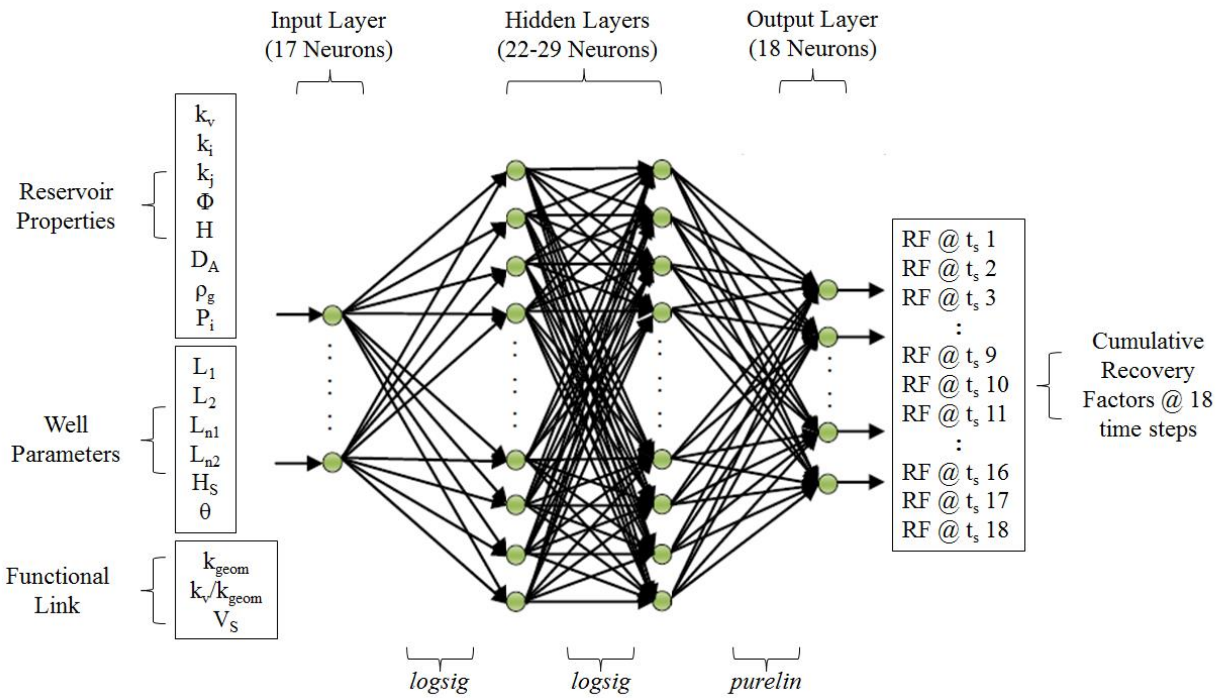


Fig. 5.8: Expanded Forward-Looking Network #18 Architecture.

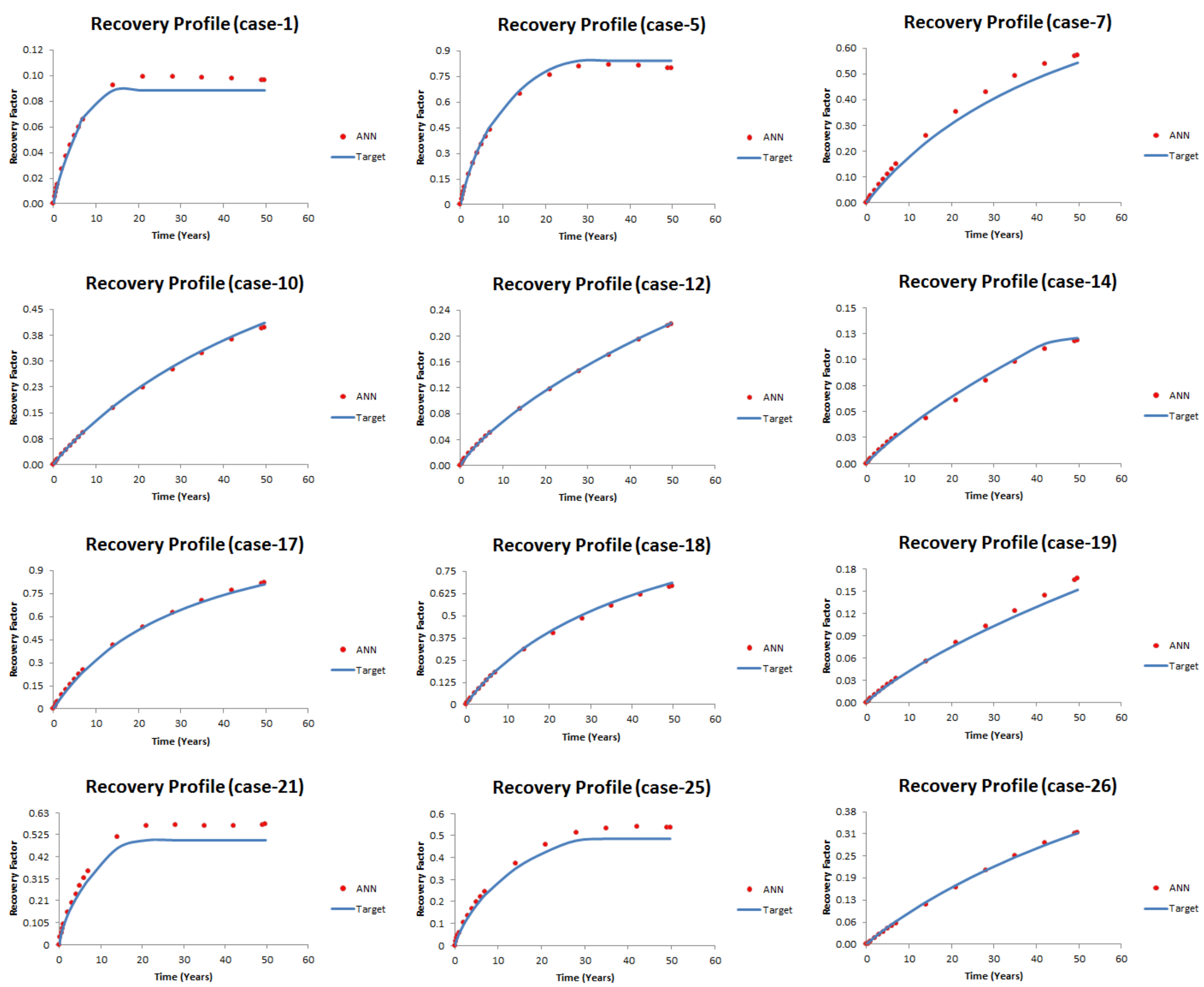


Fig. 5.9: Comparison Plots of the Recovery Profile Predictions (ANN vs. Simulator).

5.5 Inverse-Looking ANN

This section will demonstrate the development of the Inverse-looking ANN solution for the preliminary case study. The purpose was to test the feasibility of developing an expert system capable of recommending and suggesting the multi-lateral well architecture for a given set of reservoir properties and a targeted recovery profile. Therefore, the objective here was somewhat reversed from the forward-looking solution, hence the name, here the reservoir properties along with the cumulative recovery factors at 18 different time steps were the inputs to the network to solve for the dual-lateral well design parameters. Similar to the forward-looking solution, the development gradually expands the base of the input layer, meaning that the number of input parameters was gradually increased to include reservoir properties that were previously set constant along with the corresponding cumulative recovery factors determined at 18 different time steps.

5.5.1 Initial Inverse-Looking ANN Solution

Similar to the initial development of the forward-looking solution, the contents of **Tables 5.2** and **5.4** were used for extracting the input and output parameters for the network however with a different order. In this case the reservoir properties, i.e. the normal and lateral permeability and their ratios, combined with the corresponding cumulative recovery factors produced by the numerical simulator at 18 different time steps were the input parameters to the network with 21 neurons. Whereas the dual-lateral design parameters were the desired targets or output layer of the network with 6 neurons.

Many ANN scenarios were explored by varying the number of hidden layers, number of neurons per hidden layer, and the choice of transfer, training, and learning functions until the minimum error criteria was achieved. The ANN model consisted of 21 input neurons, two hidden layers with 45 and 26 neurons respectively, and 6 output neurons as illustrated in **Figure 5.10**. The log-sigmoid **'logsig'** and linear **'purelin'** transfer functions, the Bayesian regulation backpropagation training function **'trainbr'**, and the hebb with decay weight learning rule **'learnhd'** were applied in this network **(MATLAB®, 2011)**.

The average relative error between targets and network predictions was significantly small, only ~0.02%! which resulted in a correlation coefficient, *R*, equal to one as shown in **Figure 5.11**. However it turned out to be unworkable as the analysis indicated later on in this chapter.

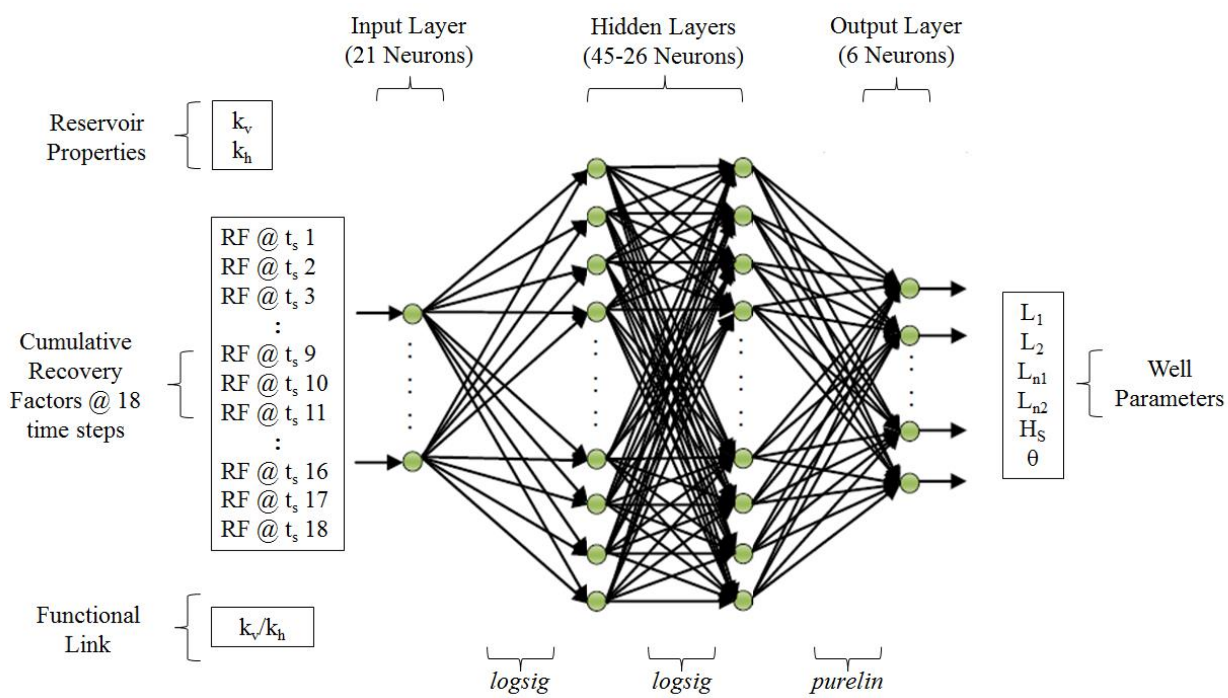


Fig. 5.10: ANN Architecture for the Initial Inverse-Looking solution.

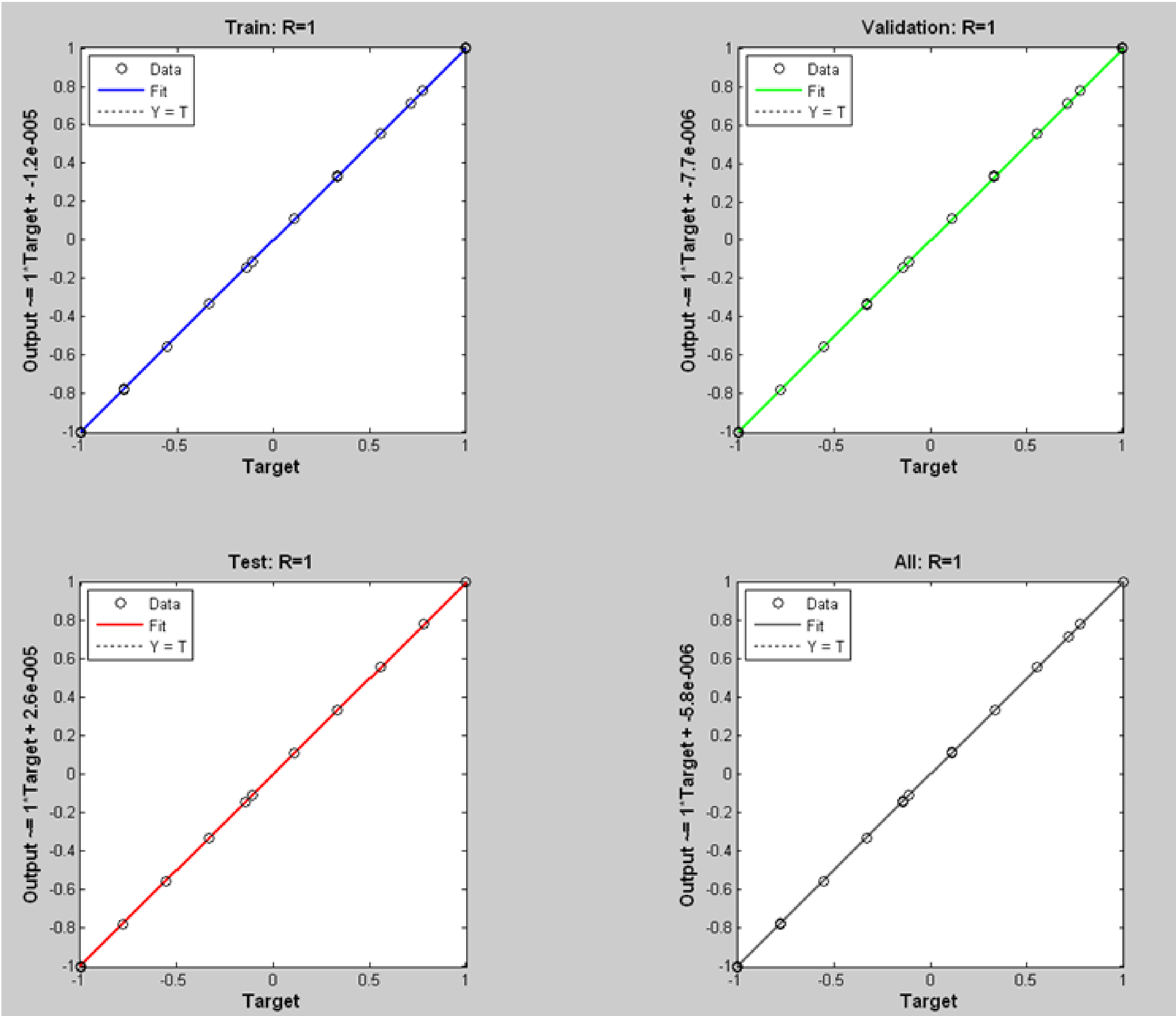


Fig. 5.11: Regression Plots for the Initial Inverse-Looking ANN solution of Fig. 5.10.

The process of randomly selecting 70% of the data set for training, 19% for validating and 11% for testing was also applied here as well. **Figure 5.12** demonstrates two parameters of the 11 tested cases which indicated perfect matches between targeted and predicted by the ANN. The other parameters comparison plots are illustrated in **Figure 5.13** which also show a perfect match.

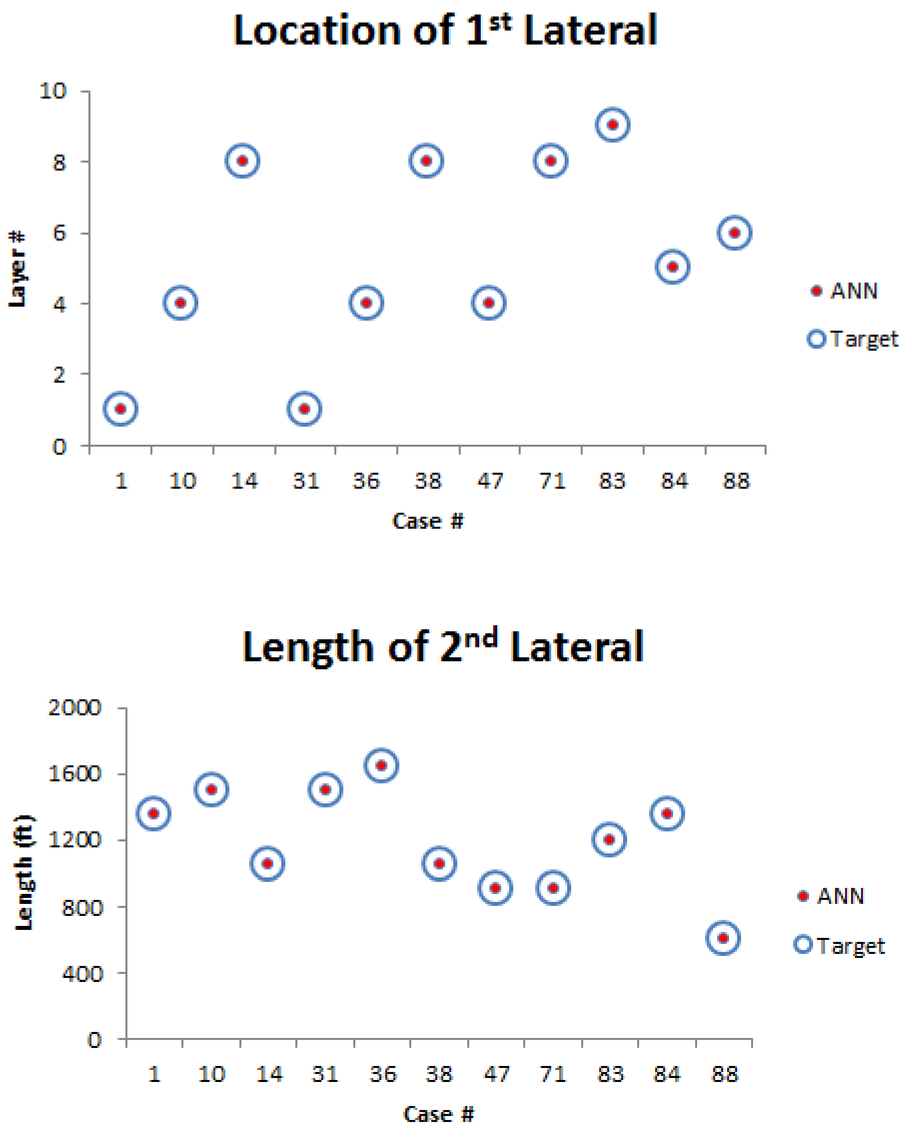


Fig. 5.12: Comparison Plots of Two Parameters for all Test Cases (ANN vs. Target).

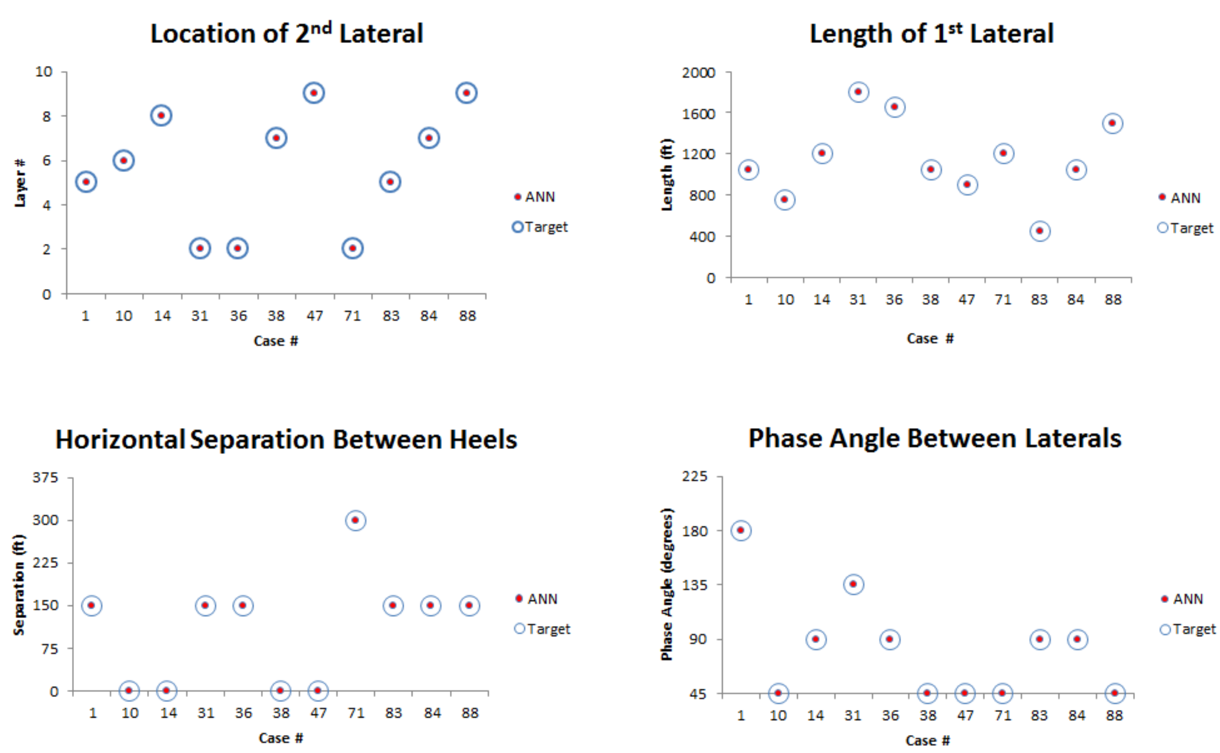


Fig. 5.13: The Remaining Parameters Comparison Plots for all Test Cases.

5.5.2 Expanded Inverse-Looking ANN Solution

The expanded Inverse-looking ANN featured a total of 27 input neurons representing 7 reservoir properties, 18 cumulative recovery factors and 2 functional links with a corresponding output layer consisted of 7 neurons representing 6 well design parameters in addition to the assigned drainage areas. Again heuristically developed a network with two hidden layers containing 24 and 31 neurons respectively as shown in **Figure 5.14**. The log-sigmoid **'logsig'** and the linear **'purelin'** transfer functions, the bayesian regulation backpropagation as the training function **'trainbr'** and the hebb with decay weight learning rule **'learnhd'** were again used for this model **(MATLAB®, 2011)**. The plots comparing the ANN predictions and the targets as well as the network regression plots are shown in **Figure 5.15** and **Figure 5.16** respectively.

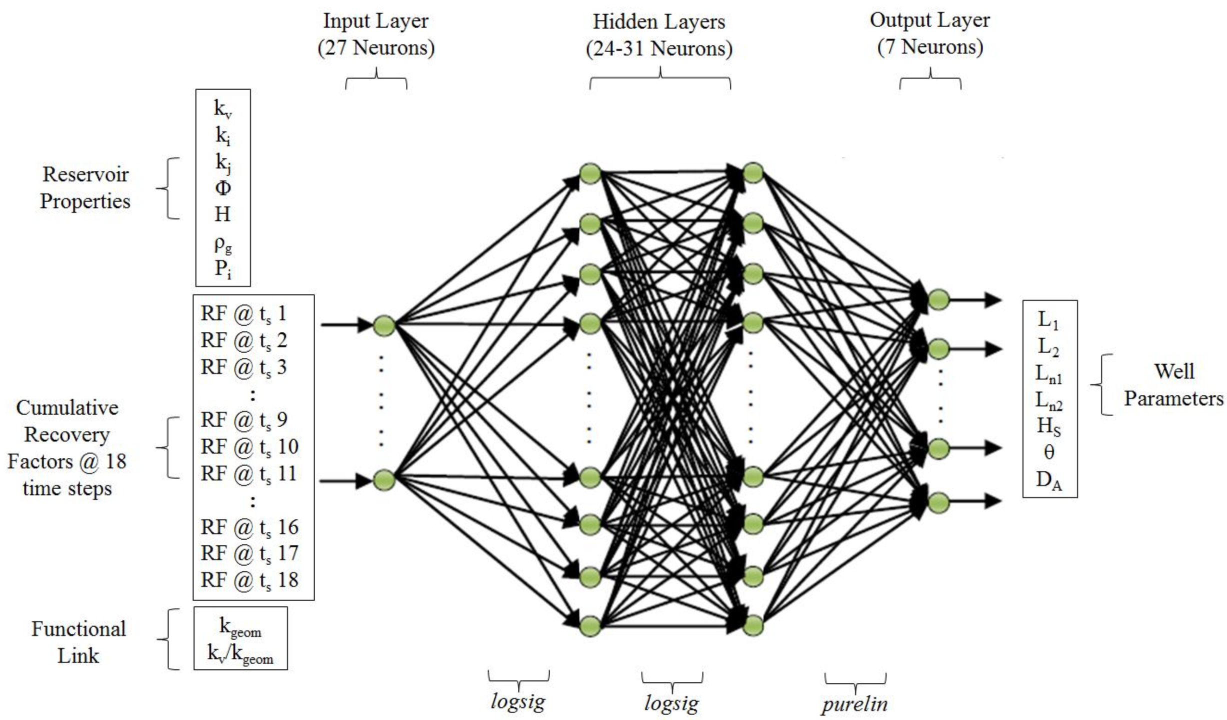


Fig. 5.14: ANN Architecture for the Expanded Inverse-Looking solution.

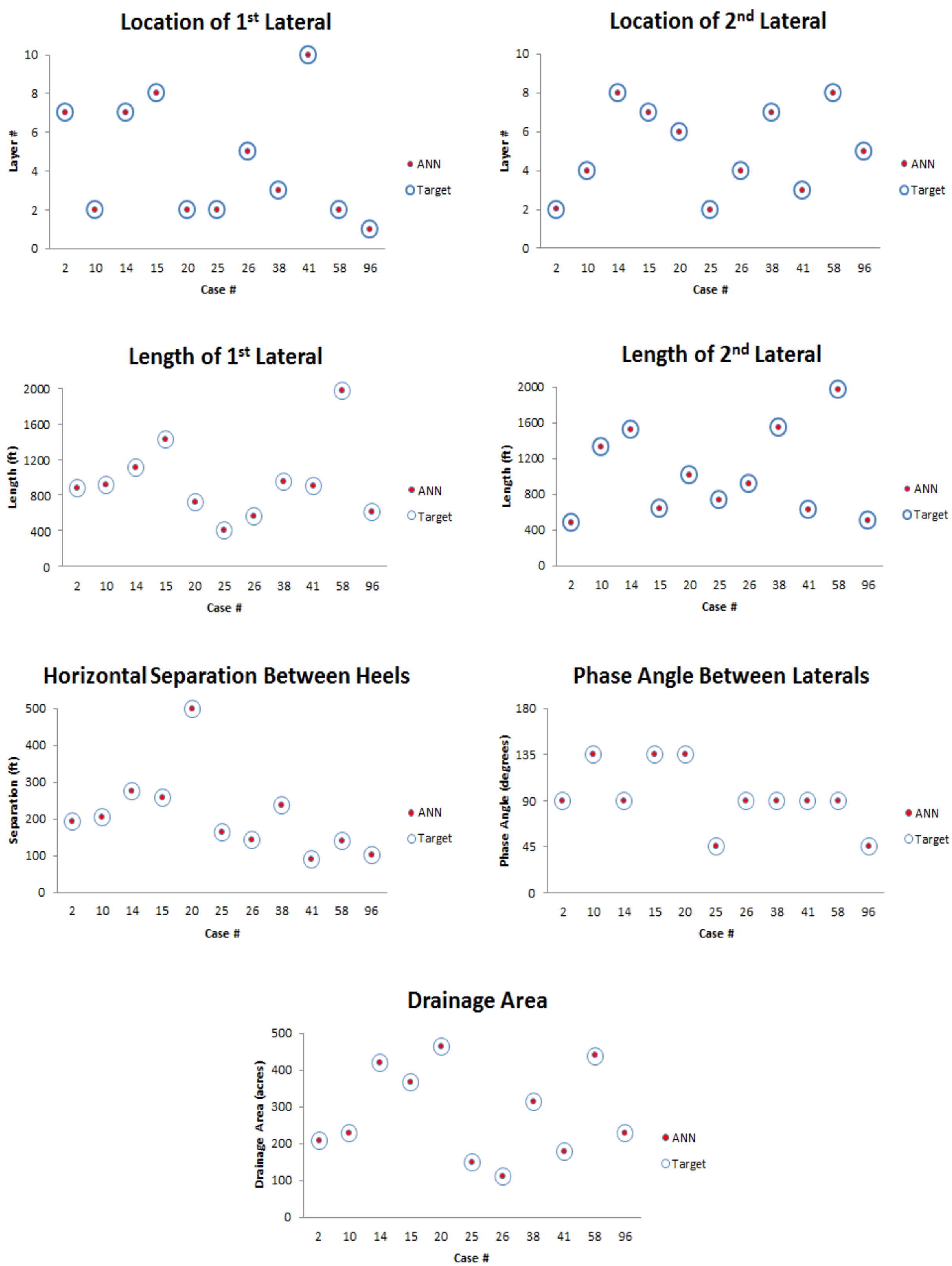


Fig. 5.15: Parameters Comparison Plots of for all Test Cases (ANN vs. Target).

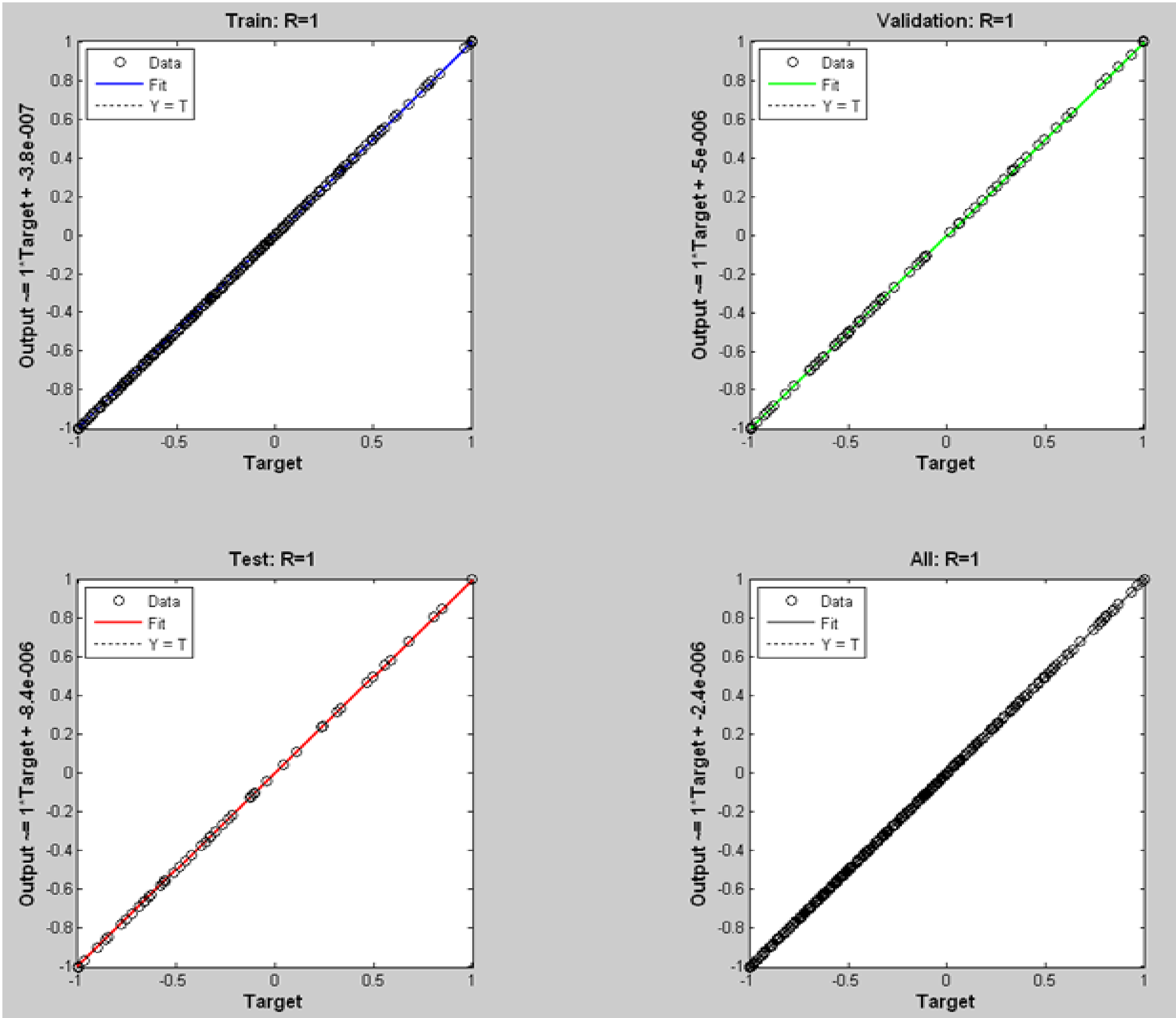


Fig. 5.16: Regression Plots for the Expanded Inverse-Looking ANN solution of Fig. 5.14.

5.5.2.1 Testing the Expanded Inverse-Looking ANN Solution

The almost perfect and too good to be true match between ANN predictions and targets obtained by the initial and expanded Inverse-looking ANN solutions triggered a flag and called for additional examinations. Testing the expanded network will suffice since it is supposed to supersede all previous inverse-looking networks. Therefore, 18 new randomly generated, data sets containing combinations of reservoir properties and dual-lateral configuration parameters each within the limits mentioned in **Table 5.5** were introduced to the numerical simulator. The cumulative recovery factors at 18 different time steps corresponding to each reservoir and well combination were obtained from the numerical simulator run. With this, the reference data base to cross check the expanded inverse-looking predictions was complete. At this point, the combination of the reservoir properties and recovery factors of the 18 new data sets were the known parameters to solve for the unknown dual-lateral parameters and assigned drainage area using the developed expanded inverse-looking network previously illustrated in **Figure 5.14**. The outputs were compared with the targets, however indicated a network failure in generalization capabilities as presented in **Figure 5.17**, hence the expanded inverse-looking network had tumbled into the overfitting trap.

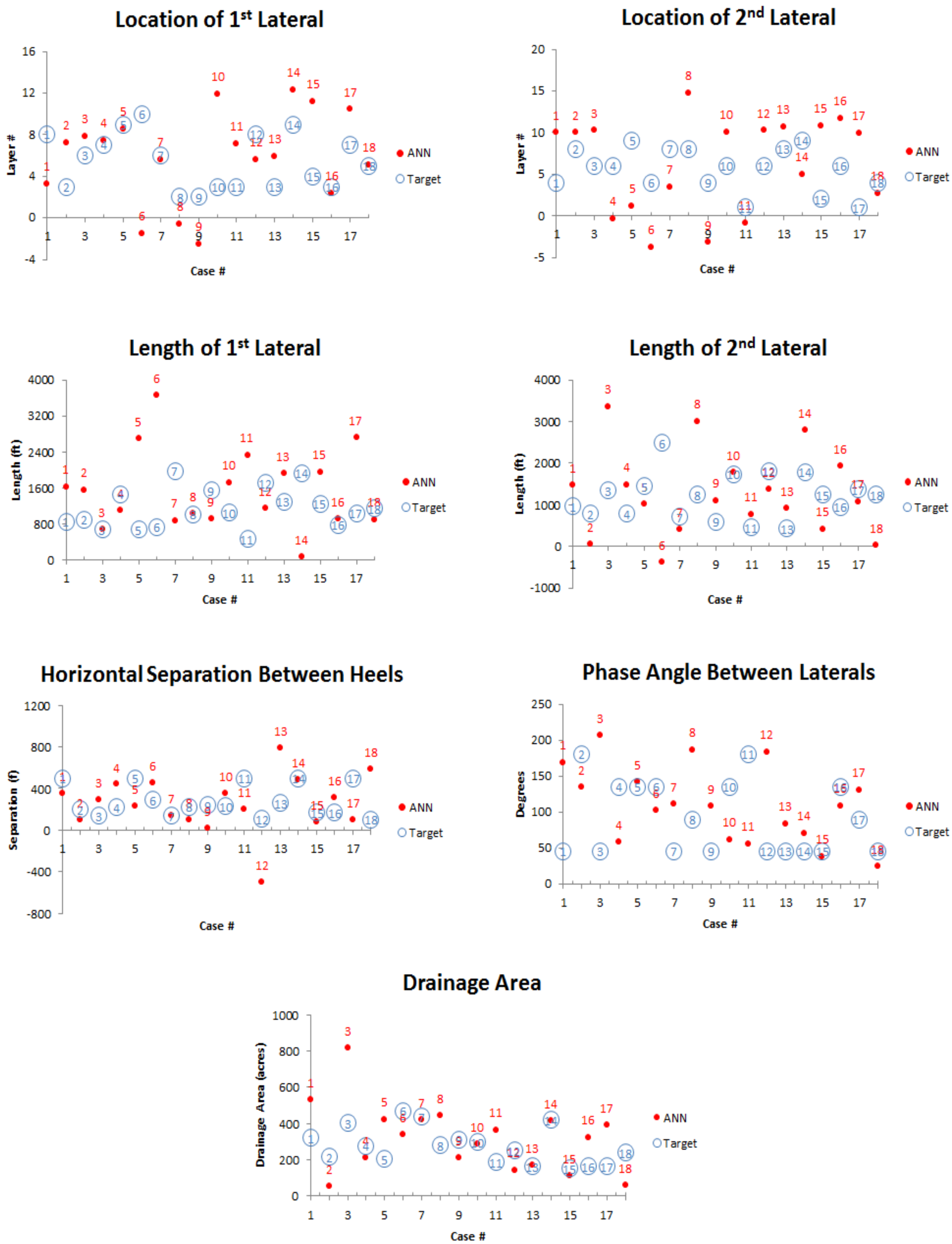


Fig. 5.17: Testing the Expanded Inverse-Looking Solution with 18 New Data Sets (ANN vs. Target).

5.5.2.2 Overfitting

When networks fail to generalize from trends and tend to memorize training data then the possibility of overfitting exists. It occurs when focus is on achieving a very small error on the training set, however the error is large when new data is introduced to the network. There are a few methods for enhancing ANN generalization.

One method is to use a network with the right size to deliver a good match. If the network is too large the higher the degree of complexity it generates and if it is too small the weaker it is to produce an acceptable fit. However knowing in advance how large a network should be for a particular problem is in itself a challenging task.

Another technique is known as ***early stopping*** which is the default method for improving generalization. In summary the way it works, as the name indicates, is that the network is triggered when to stop training. In more details, generally when a data set is provided to a network it is divided into three subsets namely a training set, a validation set and a testing set. The training set is used for measuring the gradient to reassign the network weights and biases. During the training phase the error in the validation set is observed. Usually at the beginning of training the error in the validation and the training sets decreases, conversely when the network starts to memorize the data hence overfits the data, the validation error increases. Therefore, when the validation error continually increases for a predefined number of iterations the network is triggered to terminate the training, then the weights and biases observed when the validation error was at minimum are resumed **(MATLAB®, 2011)**.

5.5.3 Modified Inverse-Looking ANN Solution

Taking into account the experience gained from the expanded Inverse-looking ANN and how to overcome the memorization and overfitting problems, a modified inverse-looking solution was developed. In the process a larger data set containing 1656 cases was used in training, validating and testing 35 neural networks. Those networks were varied in size, structure and functions. They had different number of hidden layers, different number of neurons and different combinations of transfer, training and learning functions. In the logical and physical sense all of the 35 networks, when tested with 26 new randomly generated data sets, had an improved prediction and generalization capability over the expanded inverse-looking solution, i.e. there were no predictions out of the previously defined ranges. Supporting this observation are the results obtained by three neural networks as shown in **Figure 5.18**. However the variation between targets and ANN outputs were still considered high.

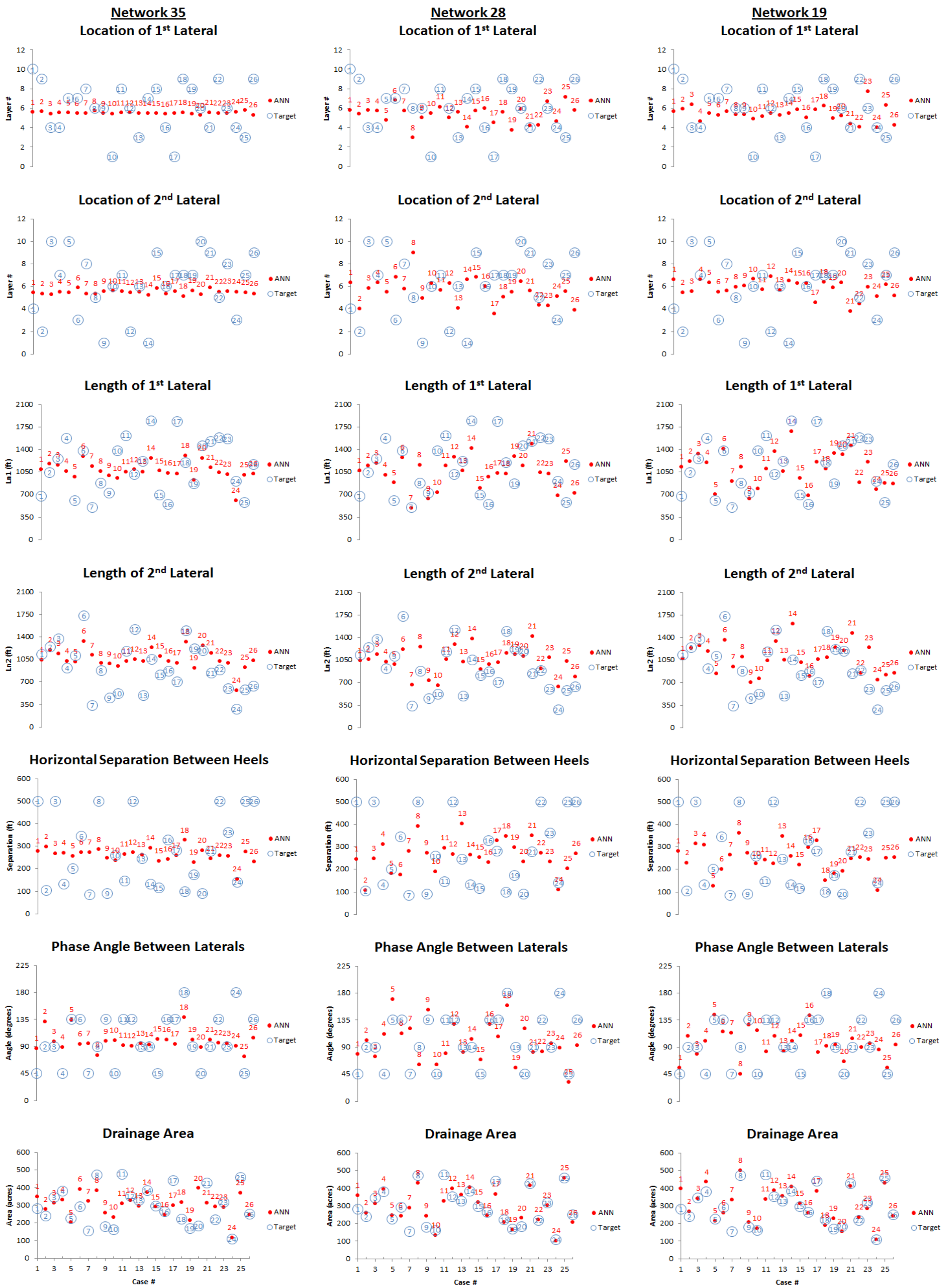


Fig. 5.18: Results from Three Modified Inverse-Looking ANNs (ANN vs. Target).

An error analysis was performed on the 35 modified inverse-looking neural networks to compare and understand their behavior. The average errors of the 26 testing cases from each network for each parameter were compared as illustrated in **Figure 5.19**.

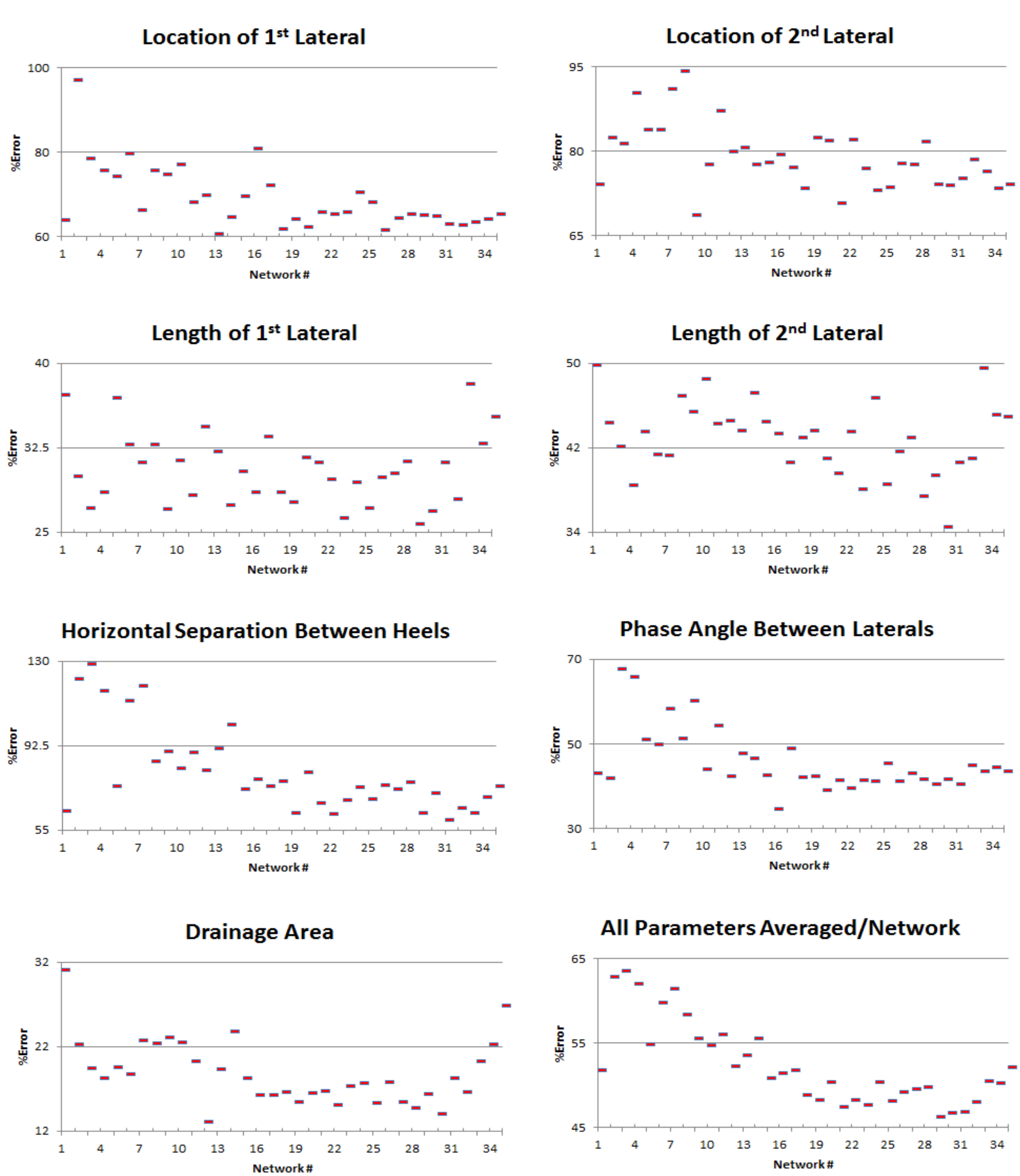
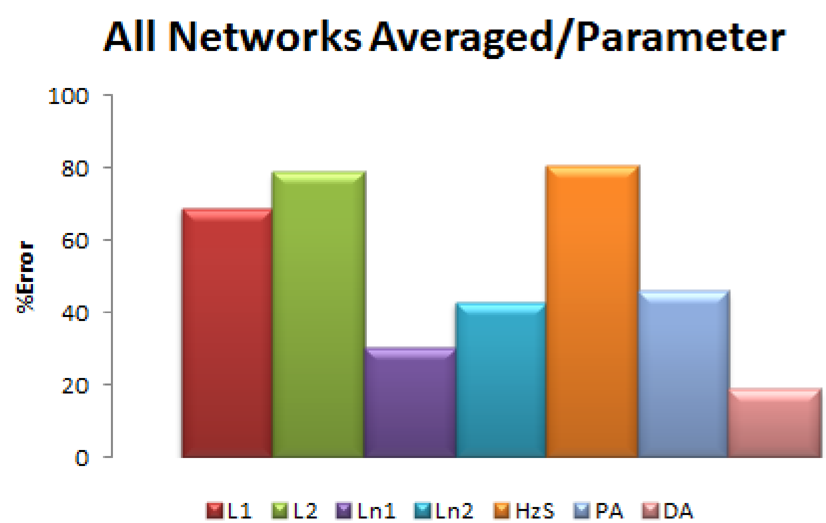


Fig. 5.19: Error Plots of Each Parameter/Network and the Total Average Error/Network.

The analysis indicates that the total average error in the horizontal separation parameter of all the networks ranked the highest whereas the total average error in the drainage area parameter ranked the lowest. Also when comparing the networks errors per parameter against the total average error of all the networks per parameter, network 19 was amongst the closest and/or below the total average error per parameter as presented in **Figure 5.20** hence it was chosen for testing a different approach as described in the following section.



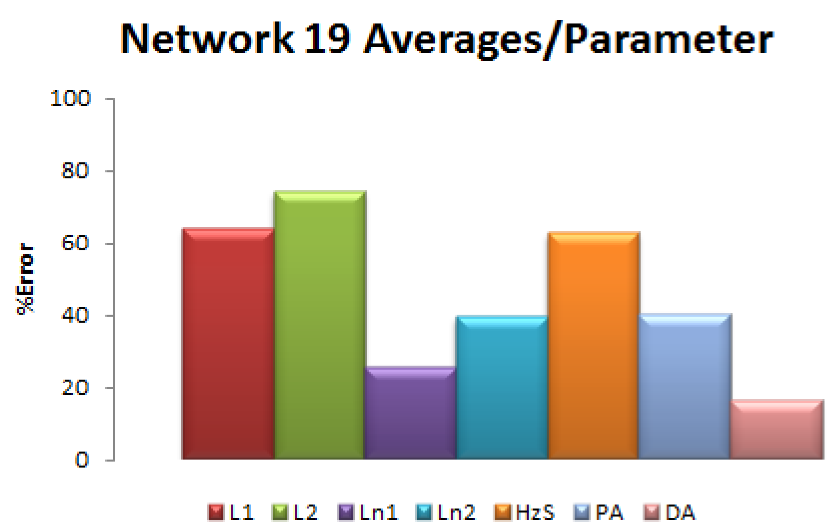


Fig. 5.20: Each Parameter Average Error of the 26 cases for All the Networks and for Network 19.

5.5.4 Closed Loop Approach

Reflecting on the original purpose of developing an Inverse-Looking ANN solution, is to predict the design parameters of a well and its assigned drainage area that will produce a target recovery profile for a given set of reservoir properties. In the previous section, the predicted parameters were compared with the targeted parameters only. However, given that this is a pattern recognition problem, there is a possibility that the combination of the predicted parameters will perform similar to the combination of the targeted parameters. In other words, there may be more than one solution that could coexist, i.e. two different well configurations could produce the same recovery profile for the same set of reservoir properties. This is a valid assumption in field development. Therefore, the proposed closed loop approach is to generate the performance of the predicted parameters combined by using the numerical simulator or the Expanded Forward-Looking solution and compare it with the performance of the targeted parameters combined. If the error between performances, i.e. target recovery profiles vs. reproduced recovery profiles, is within tolerance then it is concluded that the inverse-looking solution is successful and could be used for solving new data sets.

5.5.4.1 Crosschecking with the Numerical Simulator

The process generally is to crosscheck the modified inverse-looking networks one by one by gathering the output parameters predicted by the network combine it with their respective reservoir properties from the input set. Then use the numerical simulator to produce their corresponding recovery profiles. Compare the simulator recovery profiles to the recovery profiles located in the input set of the network and calculate the error. If the error is within acceptable limits then the network is accepted otherwise it is rejected and a new inverse-looking

ANN is evaluated. **Figure 5.21** summarizes the described process. For additional confirmation of good generalization 100 new random combinations of reservoir properties and dual-lateral parameters were generated, run by the numerical simulator and obtained their respective recovery profiles. This establishes a new data base that was not introduced during the development of the modified inverse-looking networks to use as targets and cross-referencing.

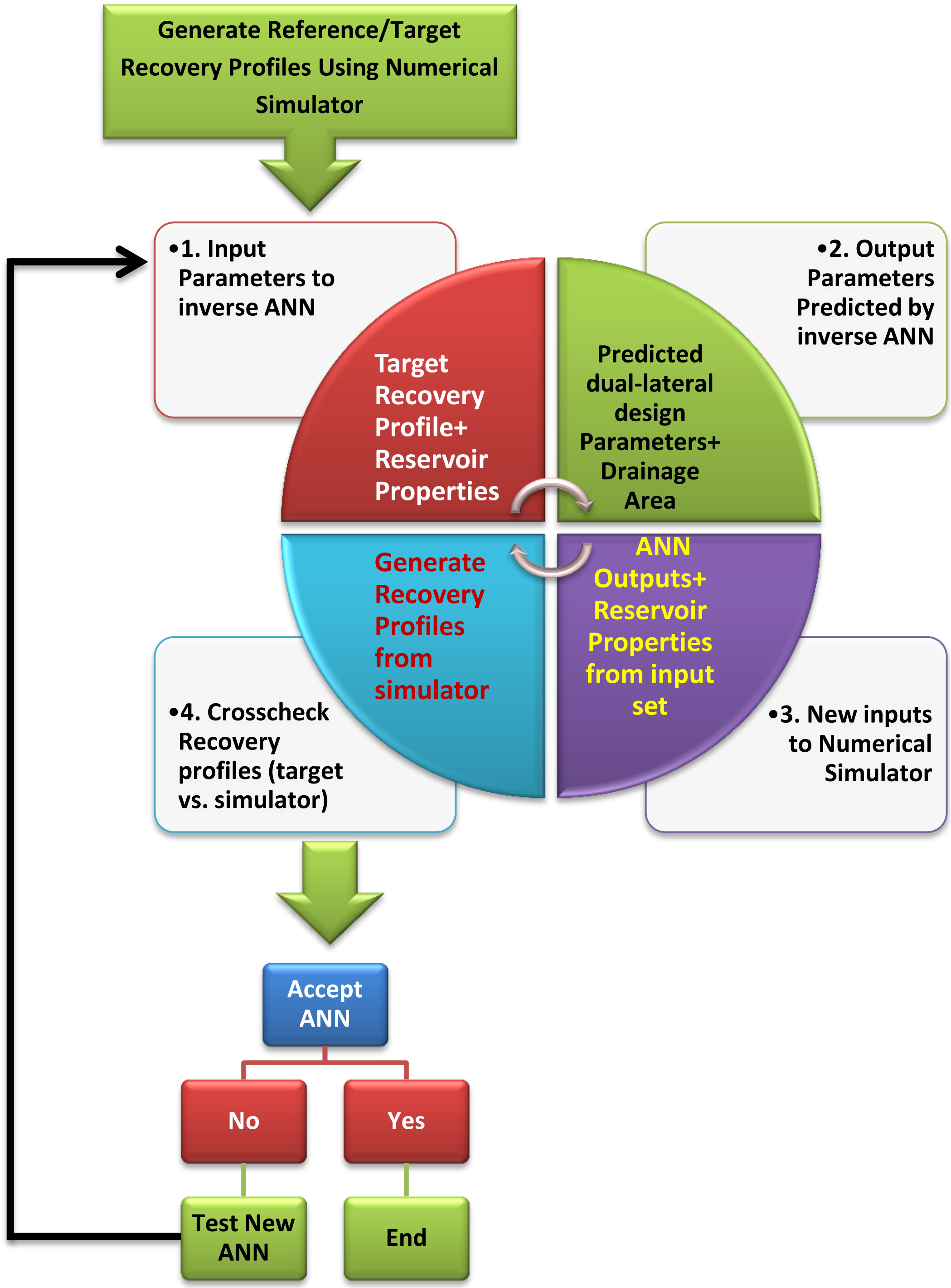


Fig. 5.21: Crosschecking Process of the Modified Inverse-Looking ANNs Using a Numerical Simulator.

As hinted in the previous error analysis section, the crosschecking process confirmed the success of network 19. An overall average error of ~12.2% was observed when comparing the 100 recovery profiles generated by the numerical simulator using the dual-lateral configurations and assigned drainage areas predicted by network 19 as new inputs and the reference/target recovery profiles used as inputs to network 19. The modified inverse-looking network 19 still had 27 input parameters and 7 outputs; it consists of two hidden layers with 15 and 22 neurons respectively as illustrated in **Figure 5.22**. The transfer functions are ***'logsig'*** and ***'purelin'***, the training function is ***'trainbr'*** and ***'learngdm'*** is the gradient descent with momentum weight and bias learning function **(MATLAB®, 2011)**.

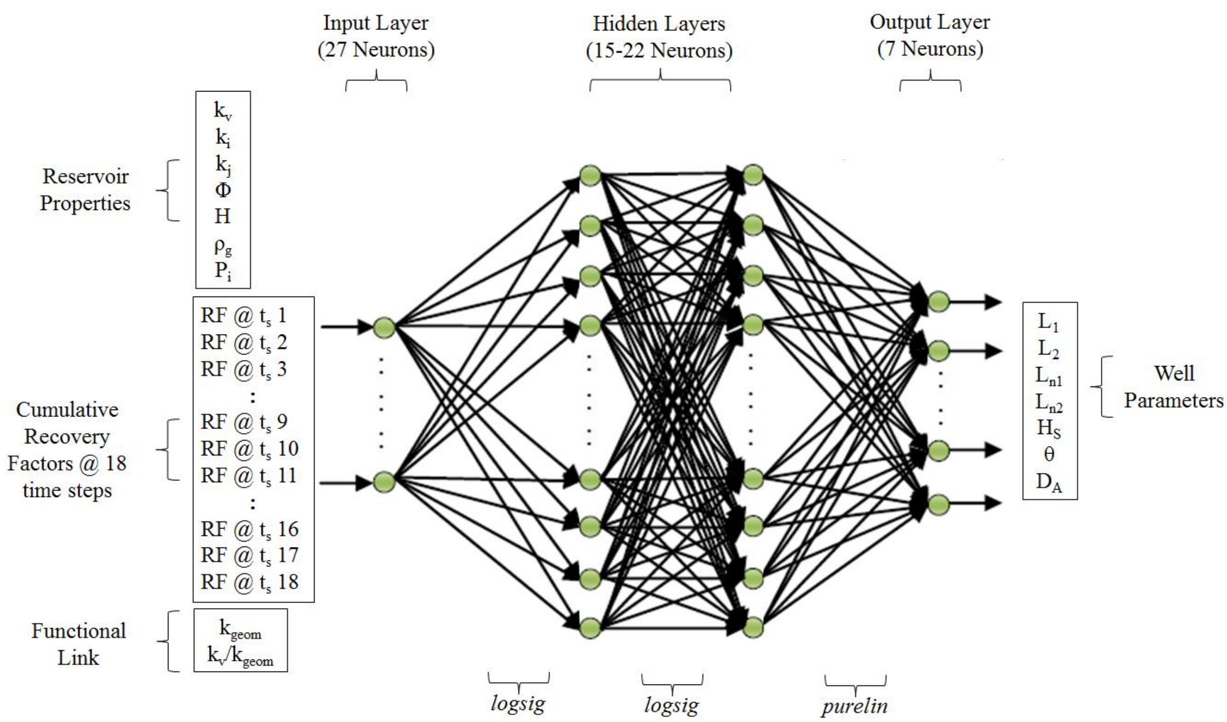


Fig. 5.22: Modified Inverse-Looking Network #19 Architecture.

5.5.4.2 Crosschecking with the Expanded Forward-Looking ANN Solution

The process is almost the same as the previous one except for the use of the numerical simulator is replaced by the successful expanded forward-looking network #18. The reason for using the forward-looking solution is in case the tool or source used for generating the reference or target recovery profiles in the first place is not available or allowed access to by the client. Also this way the robustness of both the forward and inverse looking networks will be put to the test. **Figure 5.23** highlights the process and changes made.

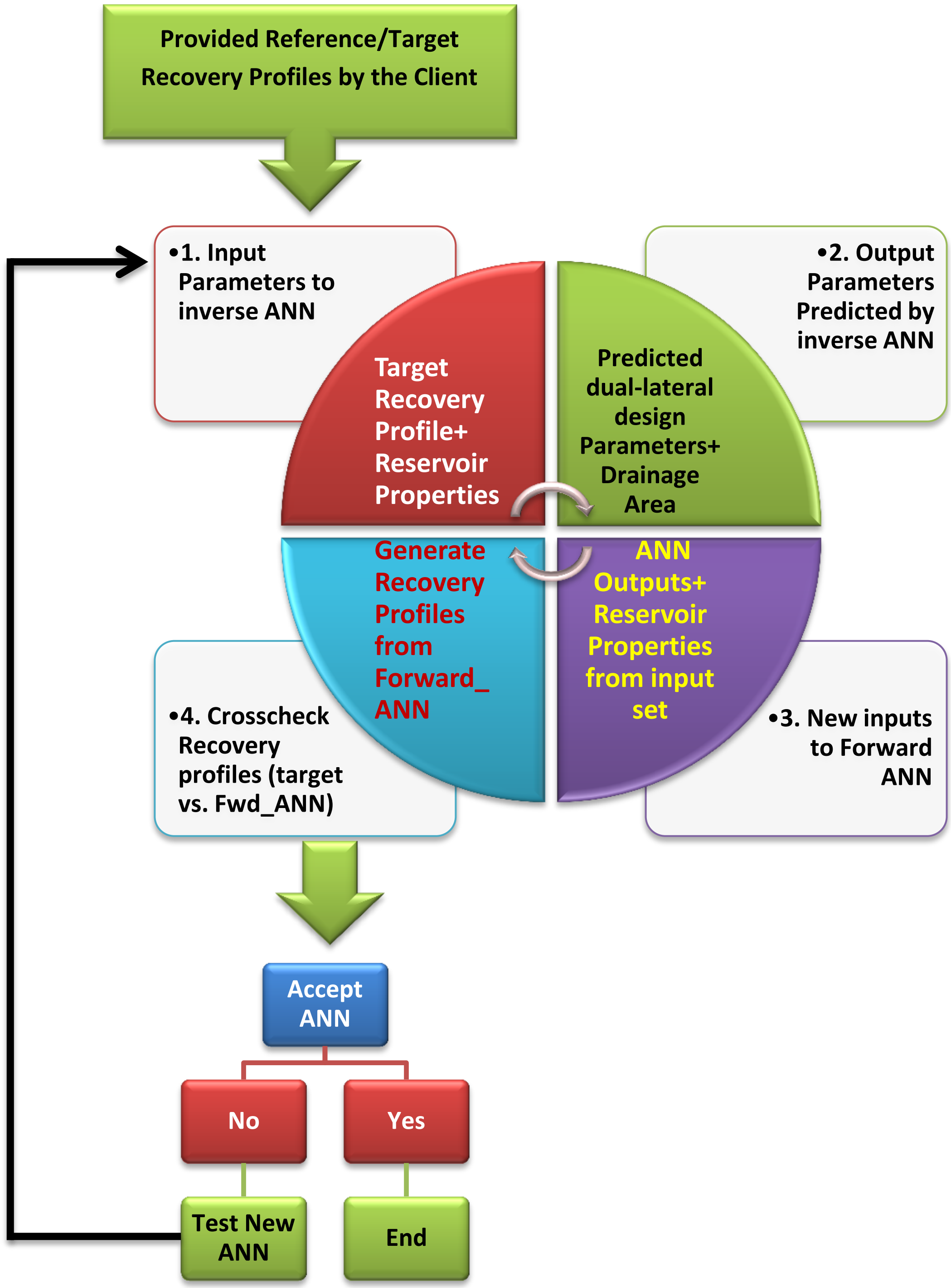


Fig. 5.23: Crosschecking Process of the Modified Inverse-Looking ANNs Using the Expanded Forward-Looking ANN Solution Network #18.

Again, the modified inverse-looking network #19 was chosen for the test since it was successful when crosschecked with the simulator. The predicted dual-lateral configuration parameters and the assigned drainage area by the inverse network #19 were added to the input set of the forward network #18 to predict the recovery profiles. Then both recovery profile sets from the target and the forward ANN were compared.

To summarize, 9 cases from the inverse network #19 results were cross-examined once using the numerical simulator and again with the forward network #18 applying the closed loop approach, described earlier. **Figure 5.24** illustrates the differences between the inverse network #19 predictions, which are the dual-lateral configuration parameters and the drainage areas, and the targeted parameters. It shows an overall average error of ~55.5% which is too high. However when applying the combination of parameters predicted by the inverse network #19 once to the simulator and once again to the forward network #18 to regenerate the recovery profiles from both tools, very good matches were achieved. An overall average error for the total 100 cases of ~13.5% was observed when using the forward network #18 and ~12.2% when using the simulator as mentioned previously, in addition the error between both crosschecking methods was evaluated at ~5.2% as displayed in **Figure 5.25**, which demonstrate a very good agreement between the forward network #18 and the simulator when having the similar inputs. The recovery profile comparison plots of the same 9 cases presented earlier are shown in **Figure 5.26**. For each case there are three curves displayed, one illustrating the originally provided recovery profiles needed to be achieved, hence called '*Target*', the other is the recovery profile obtained by using the numerical simulator where the dual-lateral parameters and assigned drainage areas are those predicted by the inverse network #19, therefore named '*Simulator*', and the red dots represent the recovery profile obtained by using the forward network #18 by assigning the same parameters predicted by the inverse network #19 to the input set and it's termed '*Forward_ANN*'.

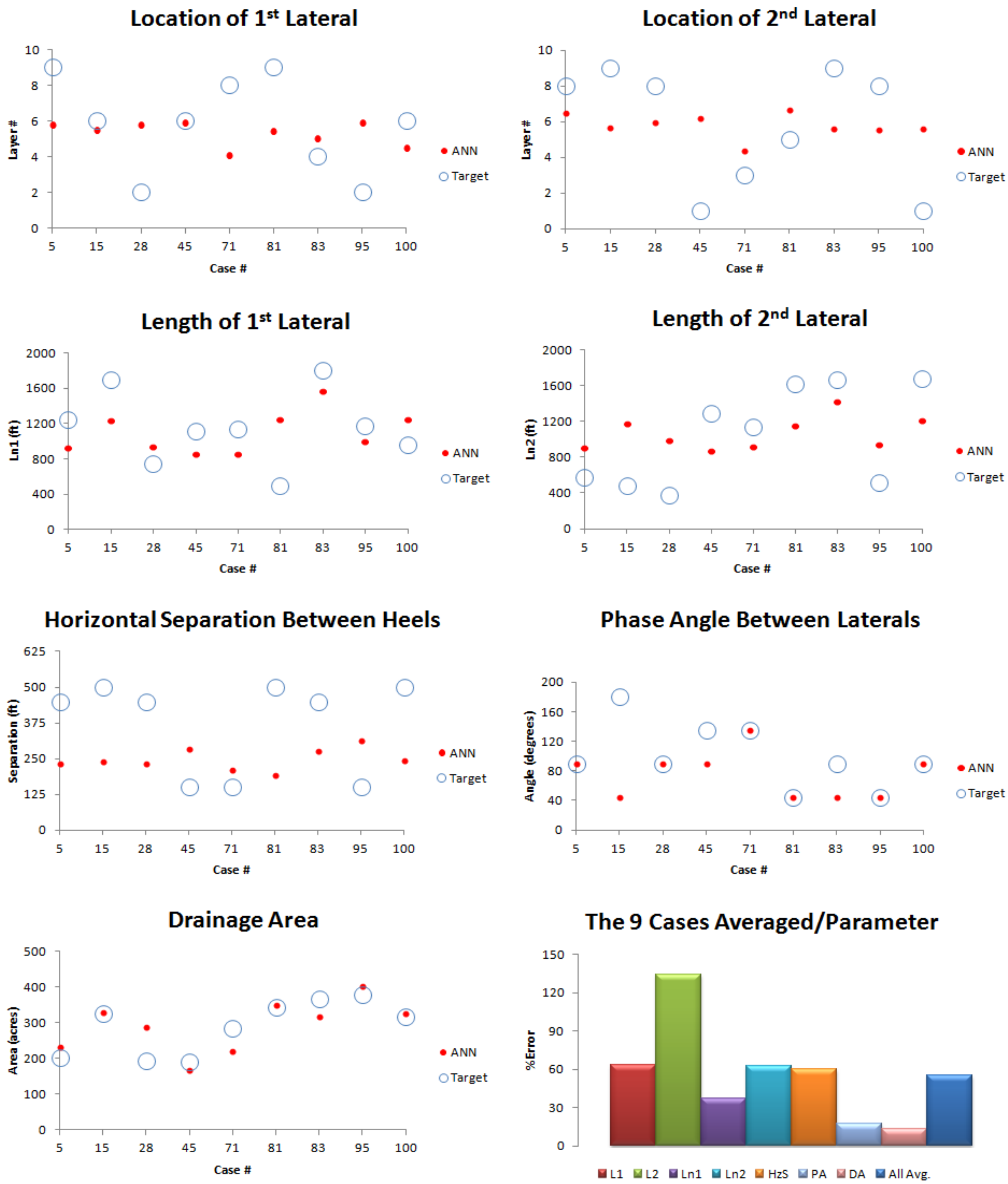


Fig. 5.24: Parameters Predicted by the Inverse-Looking Network #19 for 9 Cases and Compared With Targets.

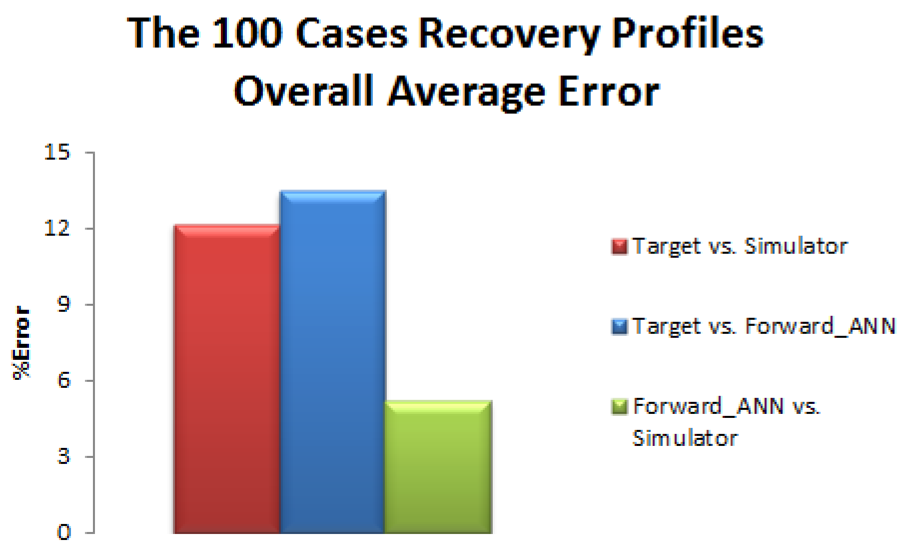


Fig. 5.25: The Overall Average Error between Both Crosschecking Methods In Addition To the Error between Both Tools.

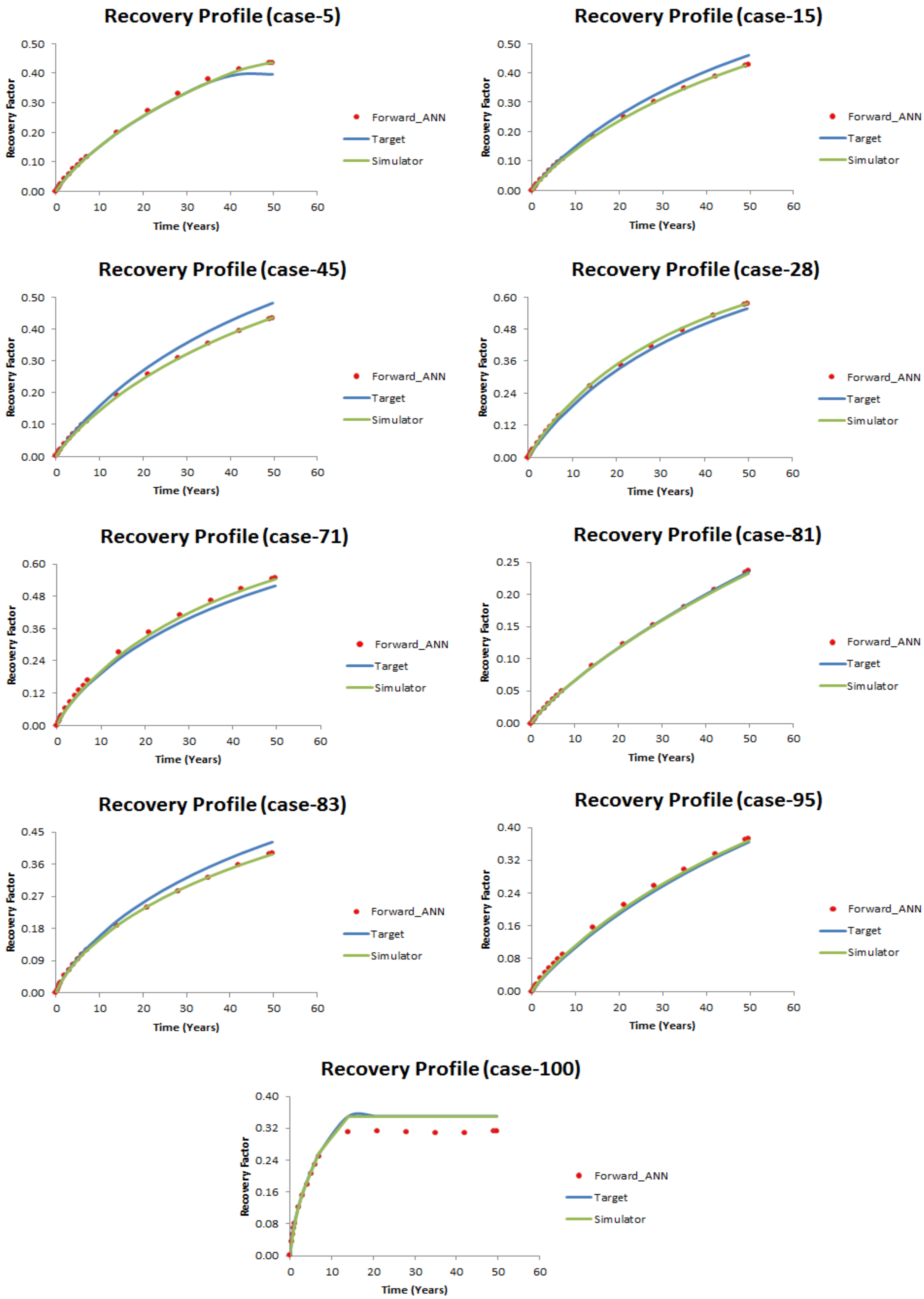


Fig. 5.26: Comparison Plots of the Recovery Profiles Predicted by Both Methods vs. the Targets for 9 Cases.

5.6 Summary and Lessons Learned

In this section the forward-looking and inverse-looking ANNs for forecasting recovery profiles and advising dual-lateral design parameters respectively were successfully developed. Both networks were tested against new data sets. The forward-looking solution for predicting cumulative recovery factors for a range of volumetric single-phase gas reservoirs completed with dual-lateral wells was tested with two new sets of data, the first containing 26 scenarios and resulted in an average error of ~7.9% and the other contained 100 cases and returned an average error of ~5.2%. The inverse-looking solution for designing the dual-lateral well configuration was also tested with new 100 cases and returned an error of ~12.2% when crosschecked with the numerical simulator, and ~13.5% when crosschecked with the forward-looking solution. In the process of achieving these goals many challenging and demanding tasks were realized and overcome by learning and developing new techniques, approaches and programs. These were instrumental factors towards the development of the multi-lateral well design advisory system and the reservoir forecasting and evaluation expert systems for the expanded form of volumetric single phase gas reservoirs and the multiphase reservoirs with bottom water drive systems cases which are presented in the next chapter. They served as a foundation of established methods and techniques that led to a smooth expansion and transition process. Some of these tasks and lessons learned were:

1. The application of a pseudorandom command for generating and populating data for any given number of cases.
2. The development of a code that loads the data sets positions the wells and assigns the reservoir properties then interfaces with the numerical simulator to automatically execute all the scenarios provided. This was a crucial time saver for generating the data bases.

3. Another code that extracts critical information from the numerical simulator outputs.
4. Encountered and overcome an overfitting and memorization problem by changing the learning function, retraining, increasing the size of the data and emphasizing ***early stopping***.
5. A closed loop approach proved the robustness of the inverse-looking solution.
6. It was observed that the training function ***'trainbr'*** and the learning function ***'learnhd'*** decrease in efficiency and takes a long time to converge when the data set is large. Therefore new training and learning functions were explored during the development of the integrated expert systems.

Chapter 6 Developed Expert Systems for Volumetric Single Phase Gas Reservoirs

This chapter explains the development and the application of a set of artificial neural networks in the area of forecasting, reservoir evaluation and multi-lateral well design. These methods are developed and implemented to volumetric single phase gas reservoirs (VSPGR) however with a variety of rock and fluid properties spanning unconventional, very tight, to conventional sands and with the flexibility of employing a multi-lateral well ranging from 2 to 5 laterals.

6.1 Forecast Expert System (FExS) Development for Volumetric Single Phase Gas Reservoirs (VSPGR)

The objective of developing this system is to deliver an acceptable performance forecast in terms of cumulative recovery factors at 18 different time steps over a period of 50 years for a given set of reservoir properties and a given multi-lateral well configuration.

6.1.1 Definition of Parameters

The parameters of **Table 5.5** were modified to include permeability ranges that expanded to account for unconventional and much tighter sands, added more laterals and their corresponding lengths and locations. **Table 6.1** lists the entire reservoir, operating and well parameters definitions, units and ranges.

Table 6.1: Reservoir, Well Design and Operating Parameters and Their Ranges

Category	Parameter	Abbreviation/Symbol	Unit/Rep	Min	Max
Reservoir	Vertical Permeability	k_v	md	1.0e-05	1.0e-4
Reservoir	Lateral Permeability in the ith direction	k_i	md	1.0e-04	0.1
Reservoir	Lateral Permeability in the jth direction	k_j	md	1.0e-04	0.1
Reservoir	Porosity	Φ	fraction	0.05	0.35
Reservoir	Total Reservoir Thickness	H	ft	10	200
Reservoir	Drainage Area	D_A	acres	100	500
Reservoir	Gas Density	ρ_g	lb/ft^3	0.04	0.08
Reservoir	Initial Pressure	P_i	psi	1500	5300
Functional link	Lateral Permeability Geometric Average	k_{geom}	md	1.0e-04	0.1
Functional link	Permeability Ratio	k_v/k_{geom}	ratio	1.0e-04	1.0
Operating	Minimum Flowing Bottom Pressure	P_{wf}	psi	500	500
Operating	Minimum Daily Gas Rate	Q_g	Mscf/d	500	500
Well	Total # of Laterals	ML	# of laterals	2	5
Well	Location of 1^{st} lateral	L_1	layer #	1	10

Cont. Table 6.1

Category	Parameter	Abbreviation/Symbol	Unit/Rep	Min	Max
Well	Location of 2nd lateral	L_2	layer #	1	10
Well	Location of 3rd lateral	L_3	layer #	1	10
Well	Location of 4th lateral	L_4	layer #	1	10
Well	Location of 5th lateral	L_5	layer #	1	10
Well	Length of 1st lateral	L_{n1}	ft/cell #	200/3	1800/12
Well	Length of 2nd lateral	L_{n2}	ft/cell #	200/3	1800/12
Well	Length of 3rd lateral	L_{n3}	ft/cell #	200/3	1800/12
Well	Length of 4th lateral	L_{n4}	ft/cell #	200/3	1800/12
Well	Length of 5th lateral	L_{n5}	ft/cell #	200/3	1800/12
Well	Horizontal separation between heels	H_s	ft/cell #	1.0e-08	200/3
Well	Phase angle between laterals	θ	degrees	45	180

6.1.2 ANN Developments with Different Data Representations

One thousand new data sets were generated using the pseudorandom code in order to include the additional parameters and ranges. During training the network many different data representations were explored to enhance the accuracy and the generalization of the network. For example, due to the tightness of some of the generated reservoir scenarios because of very low permeability, they could not produce beyond three years as a result of reaching the minimum rate cut-off of 500 thousand standard cubic feet per day or the minimum flowing bottom hole pressure of 500 psi or both. The scenarios that could not sustain production beyond 3 years were causing significant confusion to the learning process while training the network hence resulting in large errors. Systematic and heuristic approaches were simultaneously administered while reaching a successful neural network tool. A set of neural networks with 3 predefined hidden layers and transfer functions however in different order, except for the last one was always the default linear transfer function ***'purelin'***, and with different do loops that varies the number of neurons in each hidden layer were setup. Then heuristically, different data representations were submitted as inputs and targets to these networks until the ANN with the lowest error was achieved. The successful ANN had a data set of 718 cases that sustain production beyond 3 years performers, represented their respective cumulative recovery factors and permeabilities with the $\log_{10}$ of their original values. The structured ANN returned a solution with an error of 21%, the details of the network are shown in **Figure 6.1**. At this point it was sought to further evaluate its generalization capabilities on a new randomly generated data set as described in the following section.

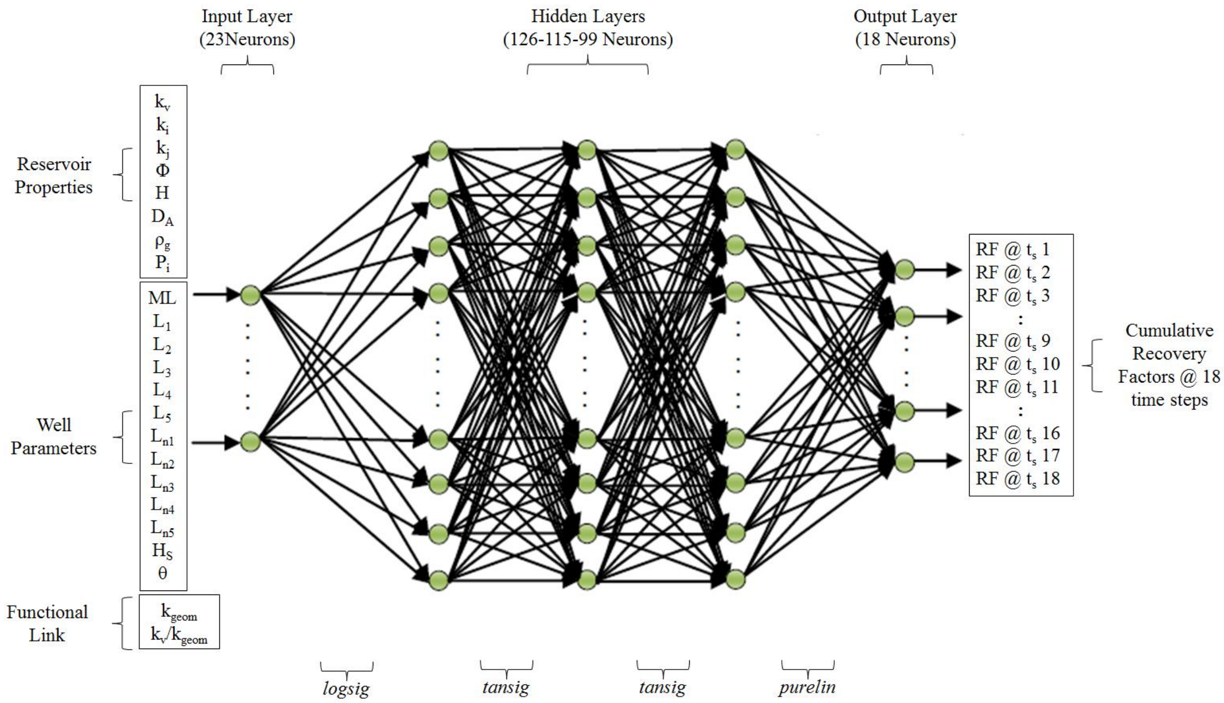


Fig. 6.1: FExS Implemented to Volumetric Single Phase Gas Reservoirs (VSPGR).

6.1.3 Testing Forecast Expert System (FExS) Applied to Volumetric Single Phase Gas Reservoirs (VSPGR)

New randomly generated data sets, 84 of them, were used to test and crosscheck the robustness of the latest developed forecast ANN presented in **Figure 6.1**. These cases consisting of reservoir properties and multi-lateral well design configurations were fed to the numerical simulator to generate their corresponding cumulative recovery factors. These results were then used as references or targets to be achieved by the forecast expert system. The cumulative recovery factors predicted by the forecast expert system had an overall average deviation from the numerical simulator predictions of ~20.3%. Further analysis of the results indicated that the maximum error was ~76% and the minimum was ~5% in addition to ~60% of the predictions, i.e. 50 out of the 84 data sets, had errors below average. **Figure 6.2** illustrates the frequency of the data within ranges of error.

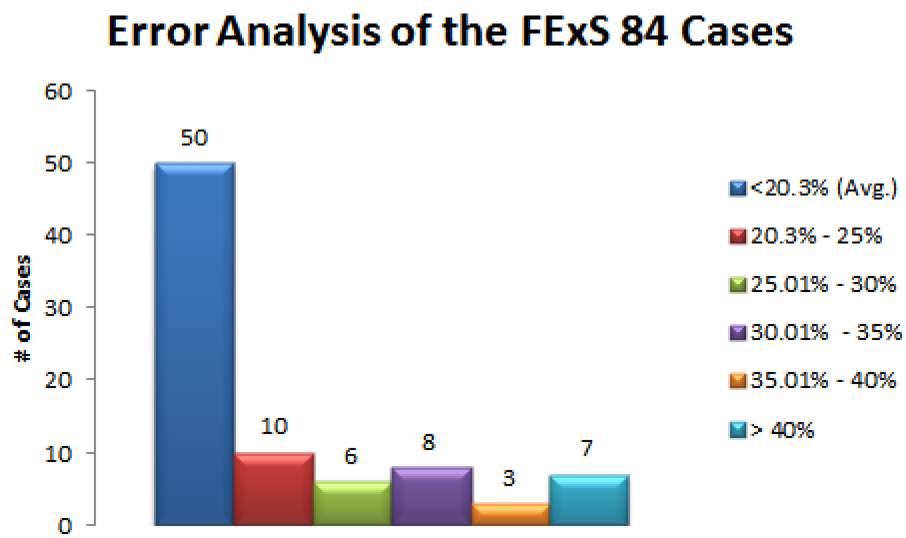


Fig. 6.2: FExS Results and Their Respective Errors Implemented to VSPGR .

Figure 6.3 presents some of the cases comparing target recovery profiles (generated by the numerical simulator) and the FExS profiles (generated by the forecast expert system).

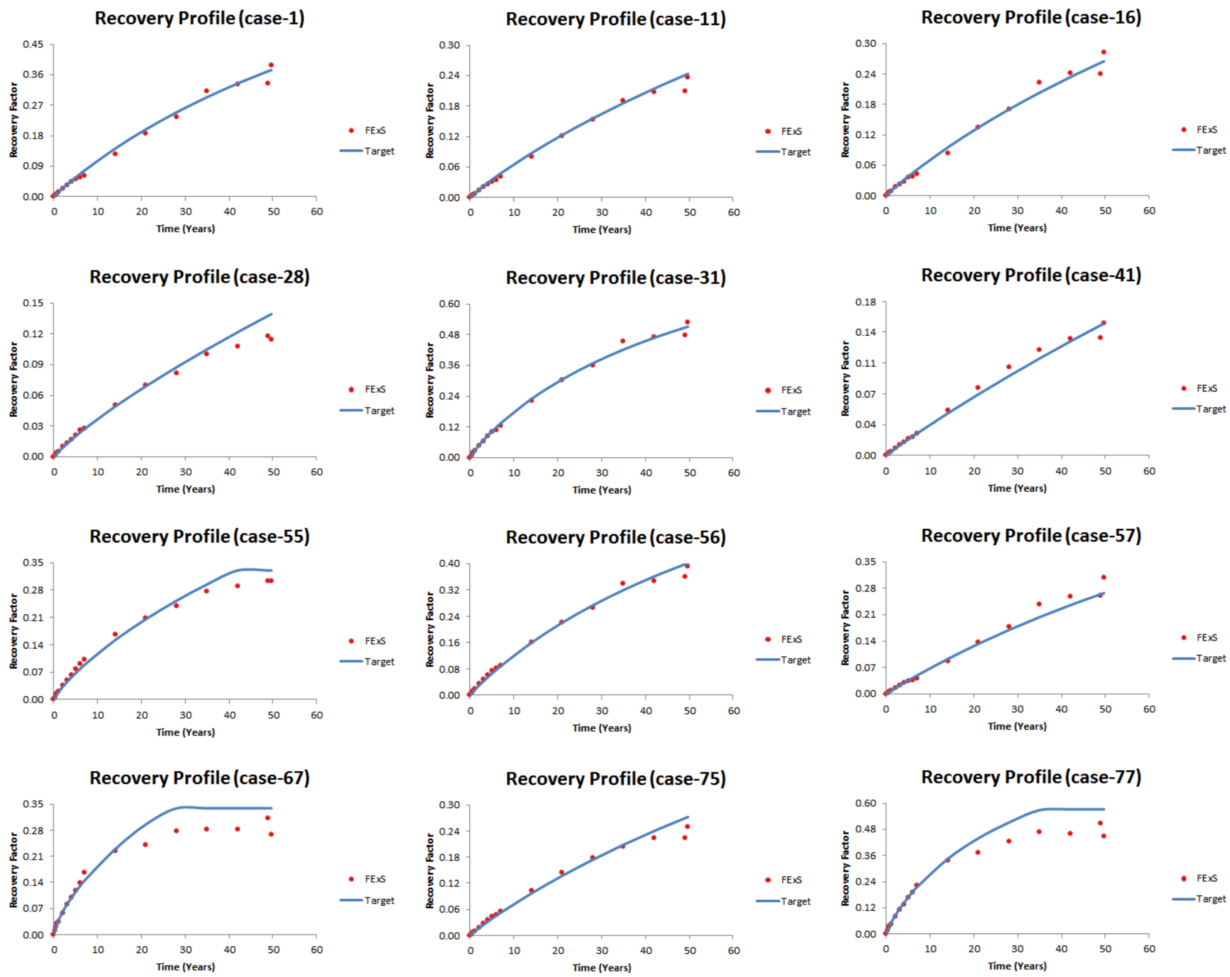


Fig. 6.3: Comparison Plots Between the Recovery Profiles Predicted by FExS and the Simulator (Target) Implemented to VSPGR.

Given the amount of cases and neural networks evaluated and reviewed the above network was delivering decent generalizations therefore was considered satisfactory to the purpose of this research.

6.2 Multi-Lateral Well Design Advisory System (MLWDAS) Development for Volumetric Single Phase Gas Reservoirs

The objective of developing this system is similar to the inverse-looking solution described in chapter 5. That is to recommend the multi-lateral well design parameters that will produce a target recovery profile for a given reservoir. However the system here is more complex in terms of increase in number of outputs required where it was only 7 parameters in the inverse-looking solution compared to 14 parameters for this system. In addition to the inclusion of much tighter reservoir systems by expanding the range of permeability to cover very low values as displayed in **Table 6.1**. Since this system is the reverse of the forecasting expert system they were simultaneously developed by rearranging the input and output parameters for each system during the rigorous scenarios explained in section 6.1.2. The ANN structure presented in **Figure 6.4**. had an error of ~36%.

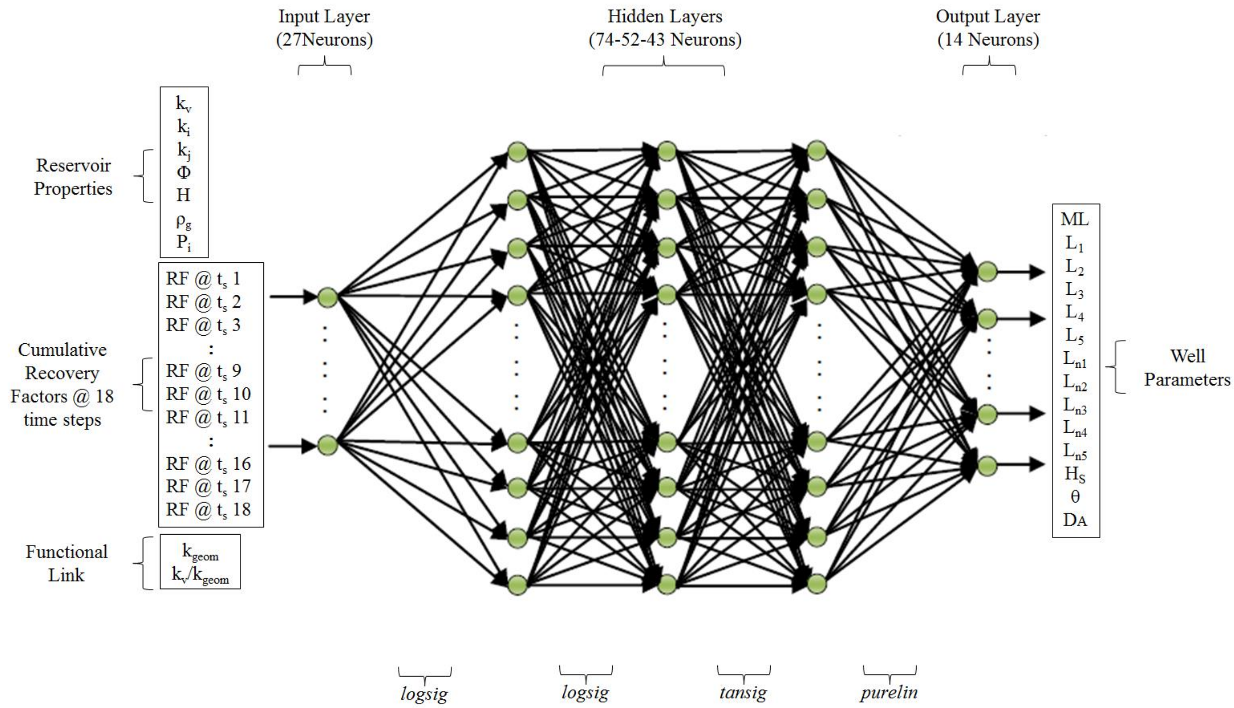


Fig. 6.4: MLWDAS Implemented to VSPGR.

6.2.1 Crosschecking Multi-Lateral Well Design Advisory System (MLWDAS) using the Numerical Simulator

Although the ANN resulted in an overall average error of ~36% it is yet not indicative enough of the robustness of the system, as proved during the inverse-looking development in Chapter 5, since there could coexist more than one multi-lateral well design that will have similar performances. Therefore the closed loop approach, described in section 5.5.4 also illustrated in **Figure 6.5**, was implemented for crosschecking.

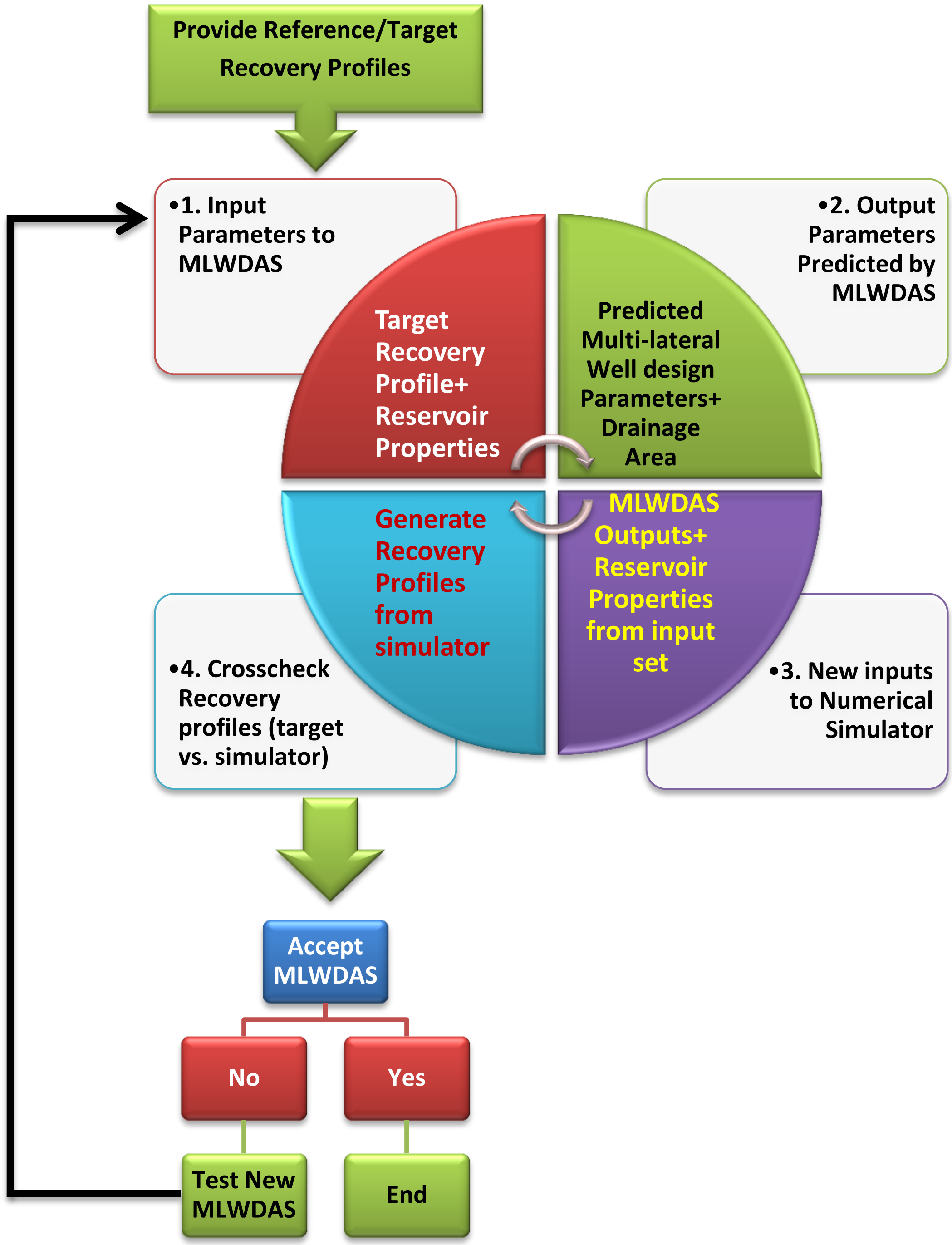


Fig. 6.5: Crosschecking Process for MLWDAS Using the Numerical Simulator.

Eighty two* of the same 84 new data sets generated for testing FExS were used for testing MLWDAS. Similarly the numerical simulator was applied to generate the corresponding recovery profiles, referred to as target, for each of the 82 reservoirs and their multi-laterals. Then the recovery profiles with their respective reservoir properties were inputs to the MLWDAS. The MLWDAS generated its recommended multi-lateral well designs and respective drainage areas for each of the 82 reservoirs. Even though these designs had an error of ~43% from the original 82 designs yet, as mentioned and proven, it is not an indicator of whether these new designs will have similar performances or not. Therefore the MLWDAS recommended well designs were combined with their respective reservoir properties and assigned drainage areas and fed to the numerical simulator to generate their recovery profiles, referred to as simulator. An overall average error of ~23.5% was measured when comparing both recovery profiles, simulator vs. target, for the 82 cases. Furthermore, 47 cases had errors less than the average error and only 13 cases had errors higher than 40% whereas the rest of the data had errors in between as shown in **Figure 6.6**.

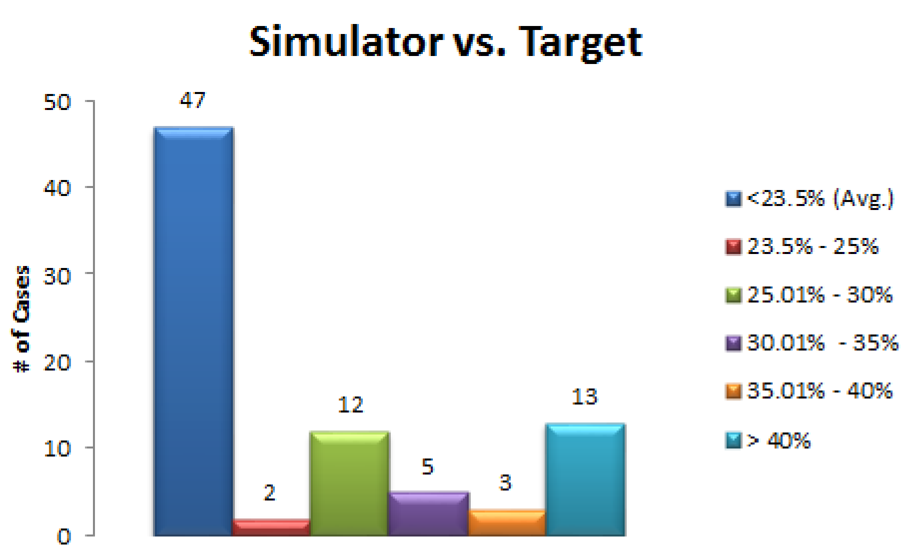


Fig. 6.6: MLWDAS Results and Their Respective Errors Implemented to VSGRs.

*the code interfacing with the simulator missed two cases hence 82 instead of 84.

6.2.2 Crosschecking Multi-Lateral Well Design Advisory System (MLWDAS) using Forecast Expert System (FExS)

Here the MLWDAS recommended well designs were combined with their respective reservoir properties and assigned drainage areas and fed to the forecast expert system (FExS) to predict their recovery profiles, referred to as FExS. Again this is a closed loop approach as demonstrated in **Figure 6.7**. This process, as said, *'hits two birds with one stone'* since while confirming that the MLWDAS recommended well designs perform as targeted, i.e. FExS vs. Target, in the same time the FExS robustness will be examined and crosschecked with the simulator results obtained from the previous crosschecking when using the numerical simulator, i.e. Target vs. Simulator.

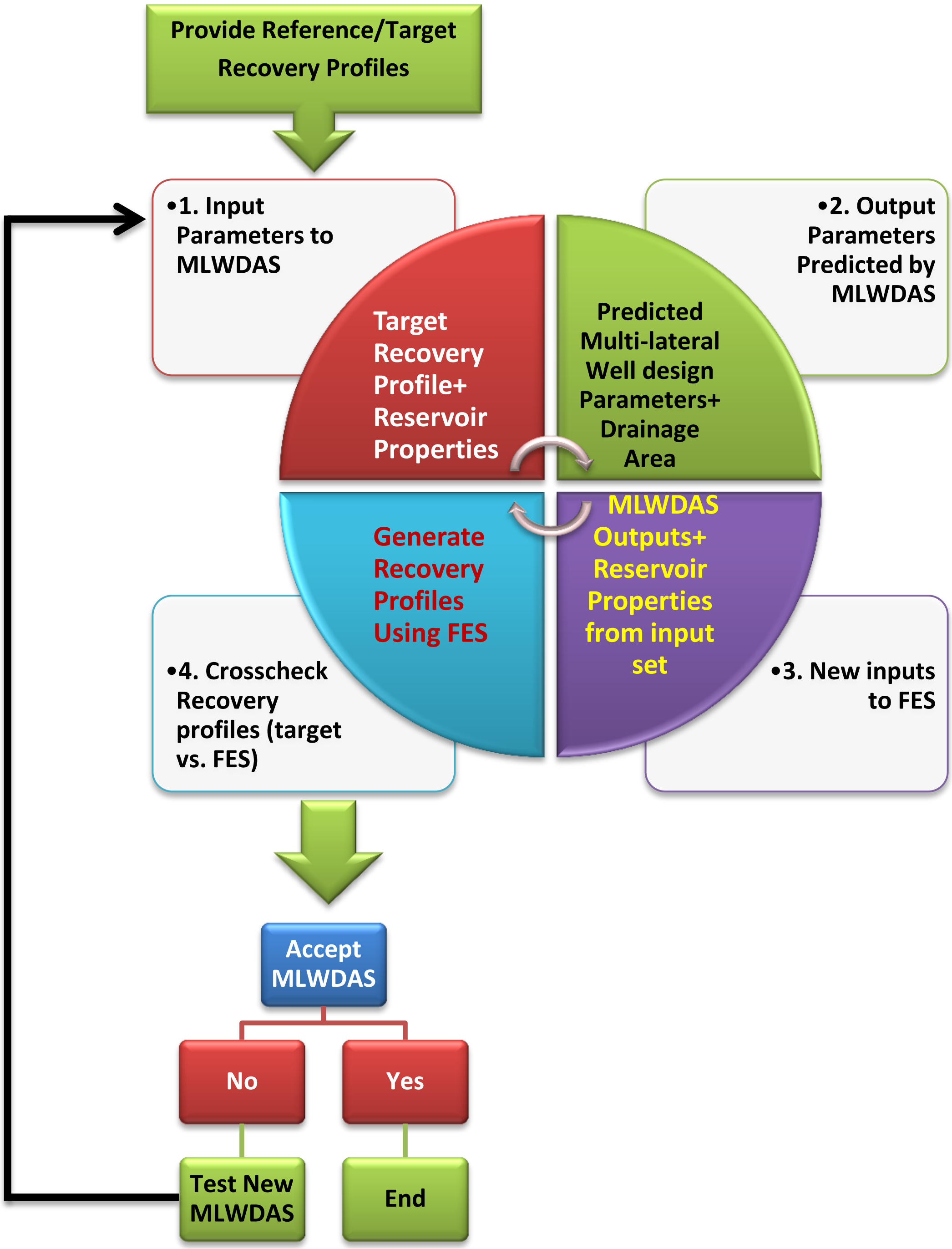


Fig. 6.7: Crosschecking Process for MLWDAS Using FExS.

FExS vs. Target

The average error was ~20.8% when comparing the recovery profiles predicted by FExS using the MLWDAS recommended well designs with the original 84 data sets recovery profiles, referred to as targets, which is considered a good generalization for most of the data. **Figure 6.8** illustrates the cases distribution with respect to their ranges of error.

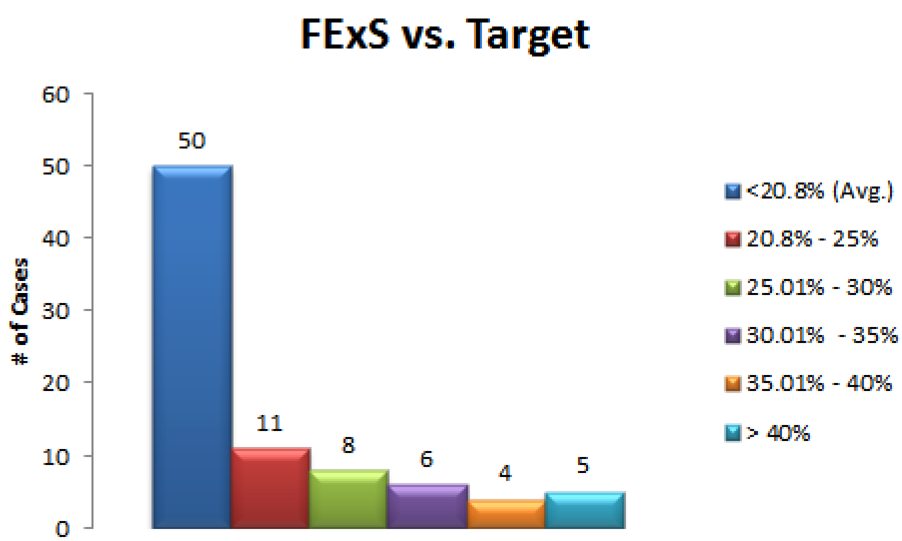


Fig. 6.8: FExS vs. Target 84 Cases Distribution with Respect to their Ranges of error Implemented to VSPGR.

FExS vs. Simulator

The average error was ~19.4% when comparing the recovery profiles predicted by FExS with the numerical simulator results when using the MLWDAS recommended well designs and the assigned drainage area as inputs to both tools. This result adds confidence to the FExS as it's in closer agreement to the simulator than to the target as it should since both of them used the same source of inputs, i.e. MLWDAS, where the target results had a completely different set of multi-lateral well designs and drainage areas. **Figure 6.9** supports this observation where more than ~76% of the cases were below an error of 25%.

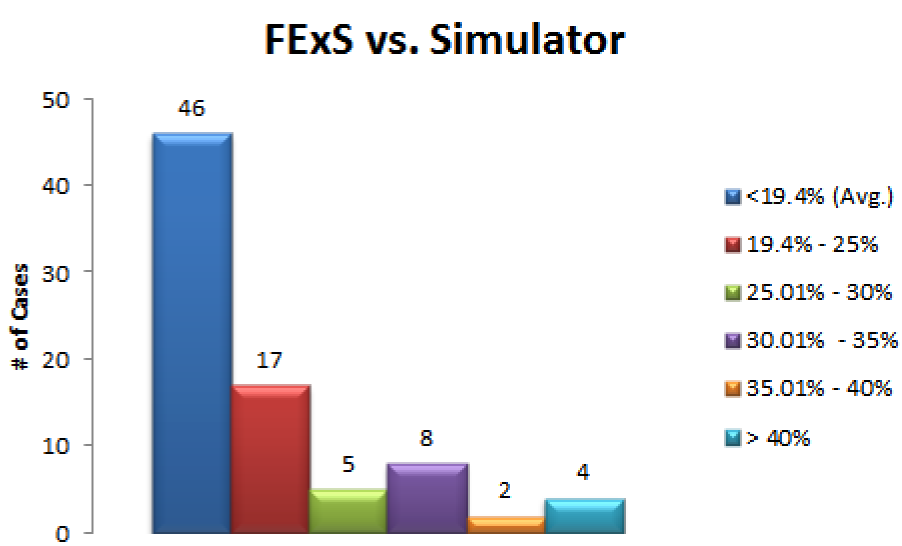


Fig. 6.9: FExS vs. Simulator 82 Cases Distribution with Respect to their Ranges of error Implemented to VSPGR.

The above analysis provided confidence in the MLWDAS recommendations capabilities. Since when applying its designs with their respective drainage areas most of the recovery profiles predicted were within an acceptable margin of error. To summarize the above crosschecking results and put them in perspective the overall average error for each process and the recovery profiles comparison plots of some of the cases are illustrated in **Figure 6.10.**

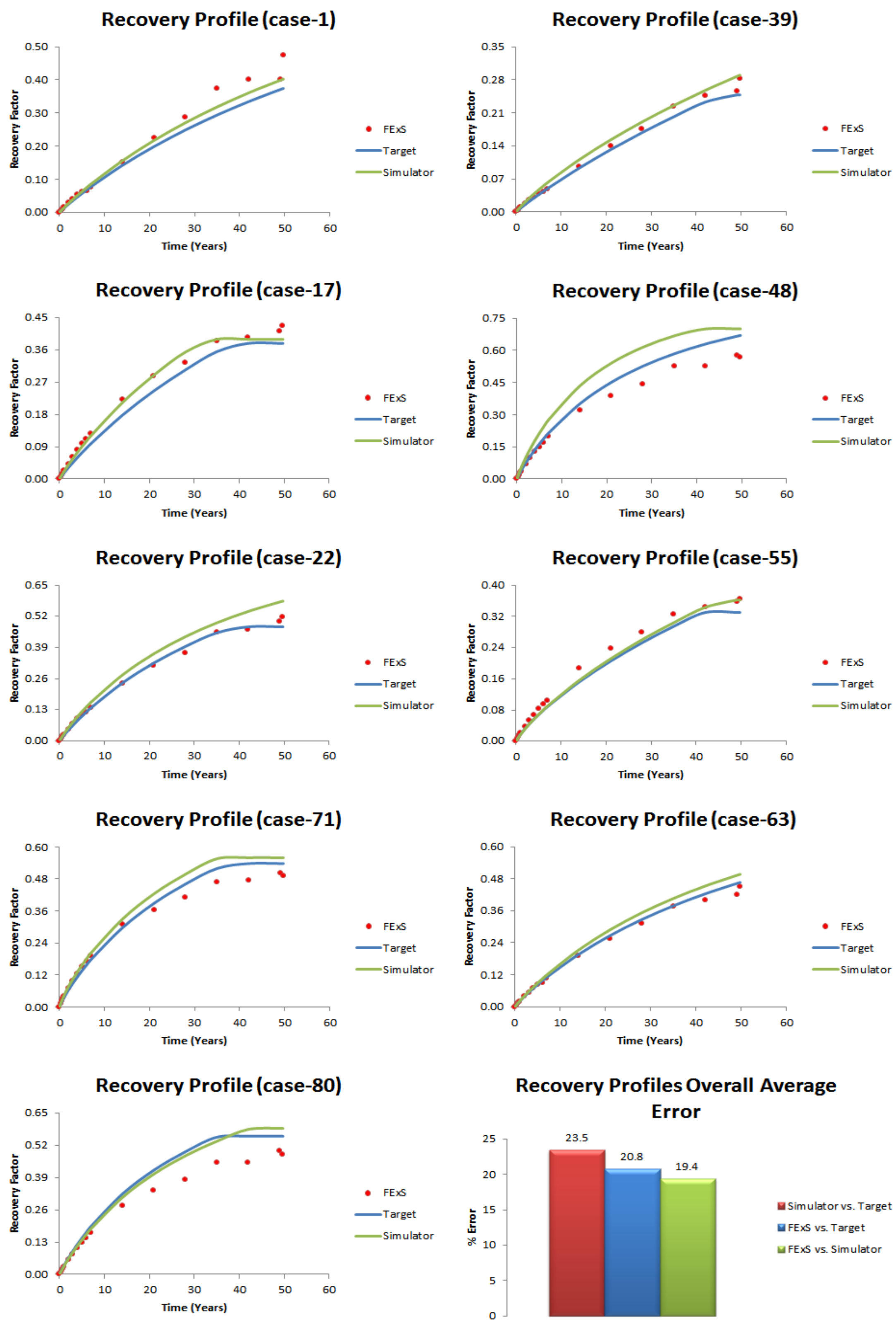


Fig. 6.10: Recovery Profiles Predicted by Both Crosschecking Methods for MLWDAS Implemented to VSPGR.

6.3 Reservoir Evaluation Expert System (REExS) Development for Volumetric Single Phase Gas Reservoirs (VSPGR)

The realizations attained in the forecast expert system (FExS) and in the multi-lateral well design advisory system (MLWDAS) led to the development of the reservoir evaluation expert system (REExS). The general theme in the previous developments thus far has been solving for one unknown. For applying the FExS, the multi-lateral design configurations and the reservoir properties were the inputs to solve for or forecast the reservoir performance, hence FExS. Likewise when using the MLWDAS, the reservoir performance and reservoir properties were required knowledge for the MLWDAS to recommend well designs. Therefore, it naturally follows the need for developing a system that will provide an assessment of the reservoir properties, hence REExS. These three entities are intertwined where a change in one would affect the other two. **Figure 6.11** provides an illustration of the overall concept and the required knowledge for using each system.

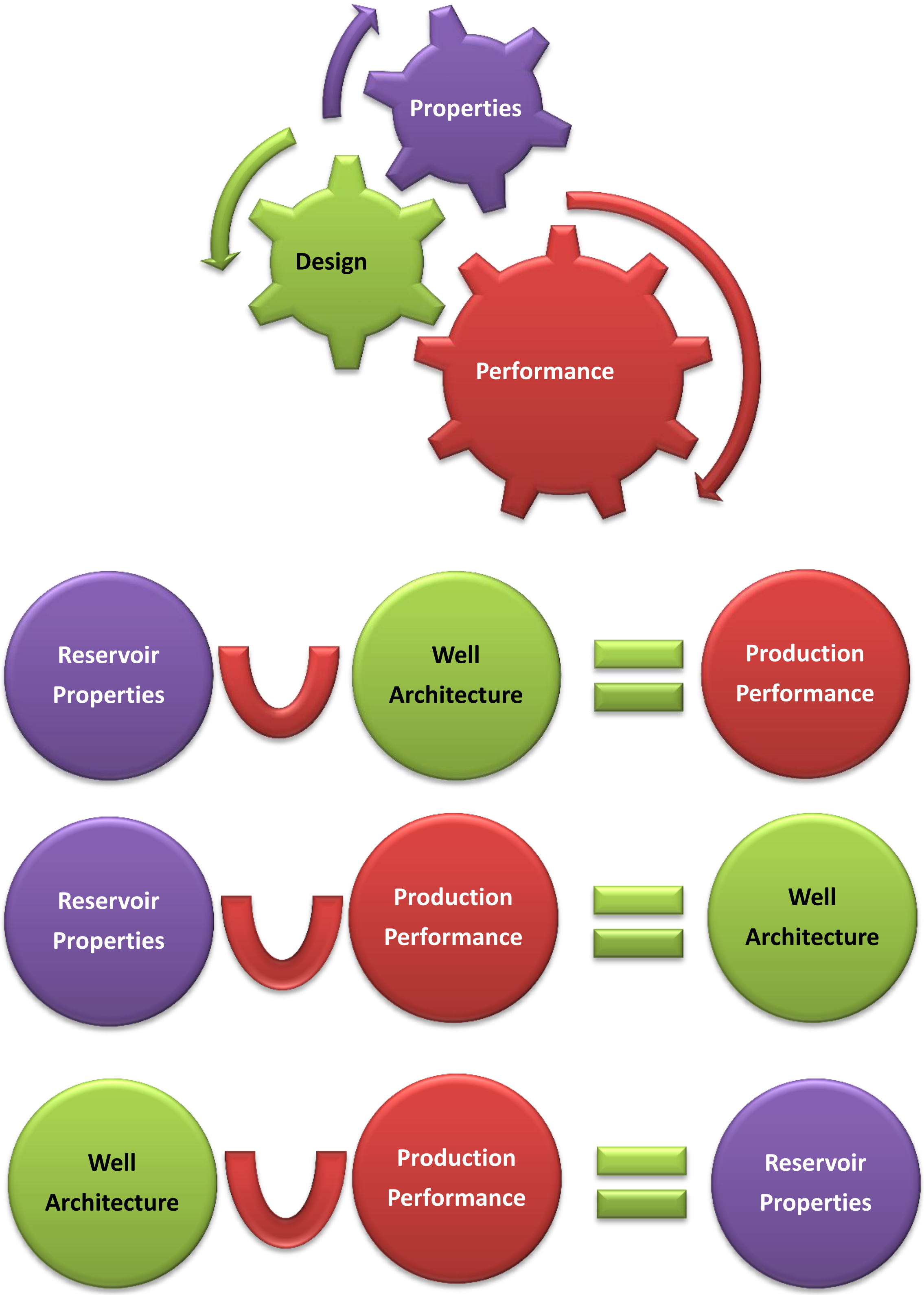


Fig. 6.11: General Theme of the Expert Systems Development Progression.

In the previous two developments, i.e. FExS and MLWDAS, it was, in concept, simply switching between inputs and outputs. However, for practical reasons, this was not the case for developing the reservoir evaluation expert system (REExS). Reasonably, evaluation of a reservoir to obtain or reassess its properties would not be of much importance when it's mature, inversely a reservoir evaluation is of great value when done earlier in its production life. Therefore, it couldn't be a matter of reorganizing inputs and outputs. Instead of the long term performances applied in the previous two developments a short term performance was required for developing the REExS.

6.3.1 Testing Reservoir Evaluation Expert System (REExS) Development for Volumetric Single Phase Gas Reservoirs (VSPGR)

To be able to develop a system that would provide an estimate of the reservoir properties early in its development. It required an early indication of its performances. Therefore the observed rate decline combined with their production periods were used for training the networks. As the previous developments, over 500 new combinations of wells and reservoir properties were randomly generated in addition to a new parameter to the ones listed in **Table 6.1** and that is the production time which ranges from 1 – 60 months. The generated scenarios combining production time, reservoir properties and multi-lateral well designs were run by the numerical simulator to produce their matching rate declines at 18 different time steps which are referred to as observed rate declines. Then the ANN was setup with the observed rate declines and its corresponding multi-lateral well designs as inputs and the reservoir properties as outputs or targets as illustrated in **Figure 6.12**.

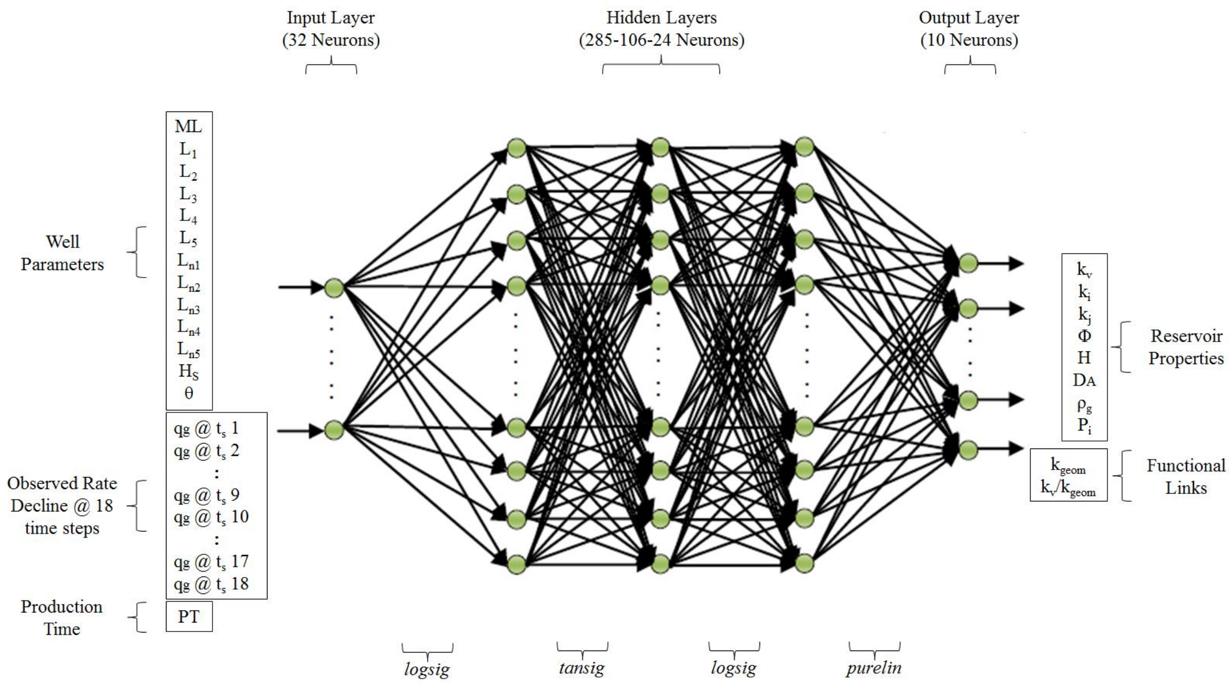


Fig. 6.12: REExS Implemented to VSPGR.

After constructing and testing many ANNs the above network was thus far used for predicting the reservoir properties. The network error was high when comparing target reservoir properties to predicted ones. **Figure 6.13** illustrates this by a sample of 10 cases showing some of the parameters discrepancies.

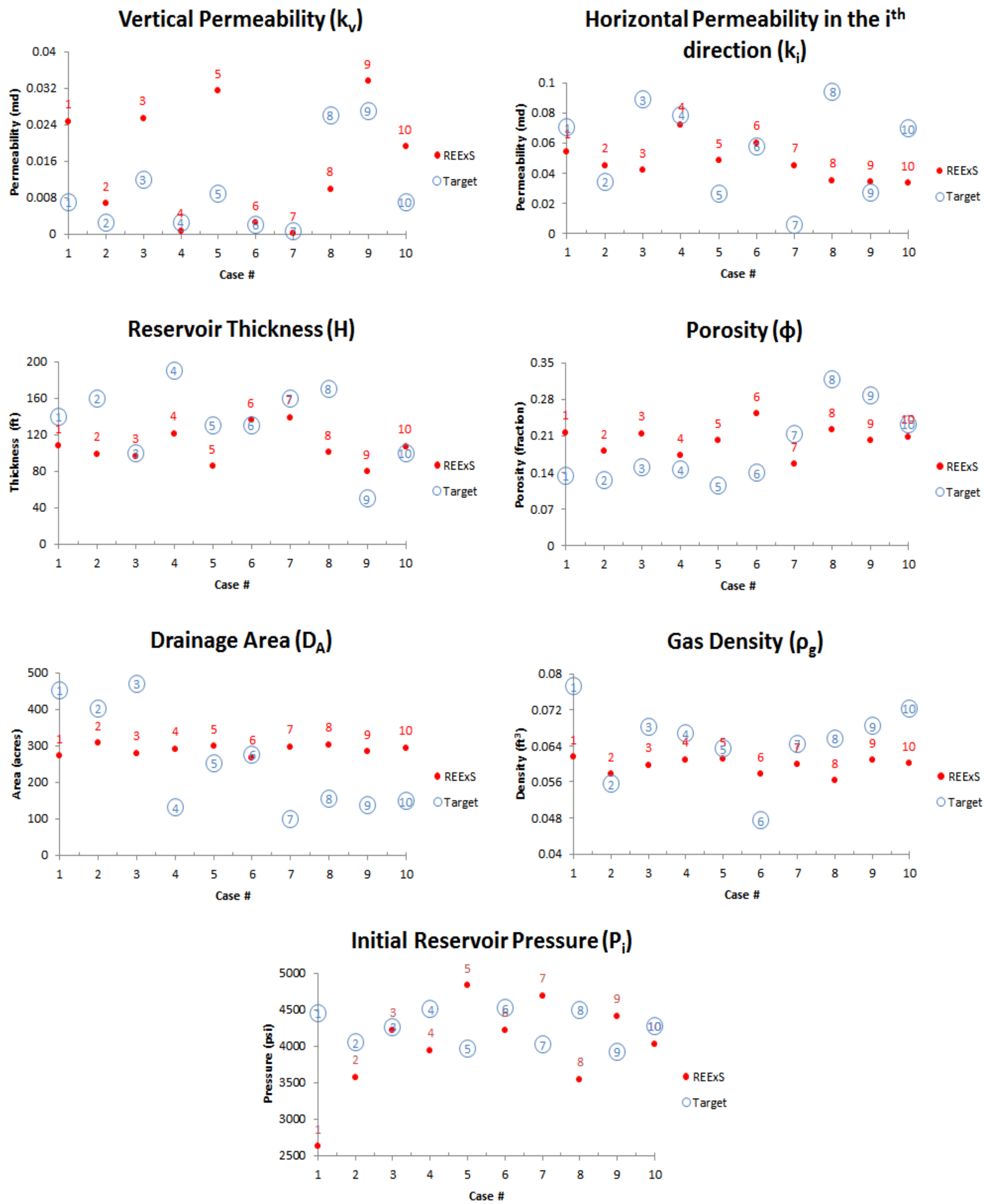


Fig. 6.13: REExS Testing Results on 10 Cases Implemented to VSPGR..

However similar to what was observed during the development of the MLWDAS where not all of the parameters could agree at once hence the conclusion of more than one solution or design that will deliver the same performance for the same reservoir, which was confirmed by the closed loop approach. Also the combination of the predicted parameters would consequently result in a close match of the observed rate decline using the same well design. Nonetheless, practically speaking, total ignorance of all of these reservoir properties is not the case in reality. There must have been some hints or basic knowledge of some of these properties that are relatively unpretentious to obtain while taking surveys and/or drilling wild cats (exploration wells). In effect these properties would be used as controlling points for estimating other properties that are arduous to gather otherwise. Hence this ANN will serve as a scientifically engineered method for adjusting unknown or uncertain reservoir parameters until an acceptable match of the observed rate decline is achieved.

To test the robustness of the system's pattern recognition capabilities the concept of the closed loop approach was implemented using the numerical simulator to crosscheck the results obtained from REExS. In addition, in case of the unavailability of a numerical simulator and to have the package integrating the expert systems function as a standalone product with a 360° approach, a Rate Decline Expert System (RDExS) was developed to allow flexibility to the engineer to cross-examine the results obtained from REExS using RDExS. Therefore, before testing the REExS, the next section will describe the development of the rate decline expert system.

6.4. Rate Decline Expert System (RDExS) Development for Volumetric Single Phase Gas Reservoirs (VSPGR)

This system could be observed as a forward-looking solution similar in concept to the FExS. As illustrated in **Figure 6.11** FExS is a performance forecasting tool which requires the knowledge of the reservoir properties and its multi-lateral well design. Similarly the rate decline is another performance indicator however for the short term and displays rates instead of cumulative recovery profiles. It is also the exact opposite of the reservoir evaluation expert system. Therefore, the order of inputs and outputs were swabbed for developing the rate decline ANN, where the reservoir properties, the production times and the multi-lateral design parameters were used as inputs to the system and the rate decline data as the system targets or outputs. **Figure 6.14** illustrates the architecture of the developed rate decline ANN.

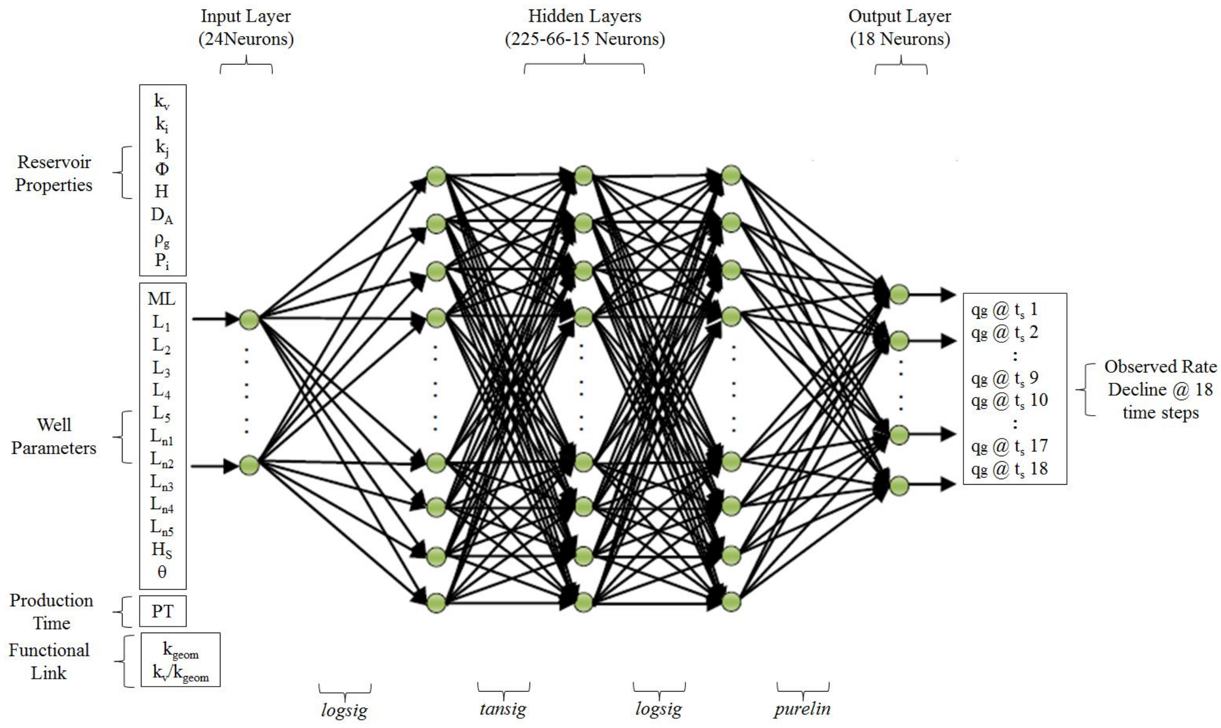


Fig. 6.14: RDExS Implemented to VSPGR.

6.4.1 Testing Rate Decline Expert System (RDExS) Applied to Volumetric Single Phase Gas Reservoirs (VSPGR)

The above network was tested with the same 48 scenarios used for testing the REExS and compared with the numerical simulator results. The overall average error was ~30% however more than ~71% of the scenarios, i.e. 34 cases, had an average error of only ~22% whereas the remaining 14 cases had an average error of ~52% which indicates that just a few cases had high errors which skewed the average error towards the high end. **Figure 6.15** illustrates the cases distribution with respect to their error ranges. With this analysis it was safe to utilize the RDExS as a crosschecking mechanism for REExS.

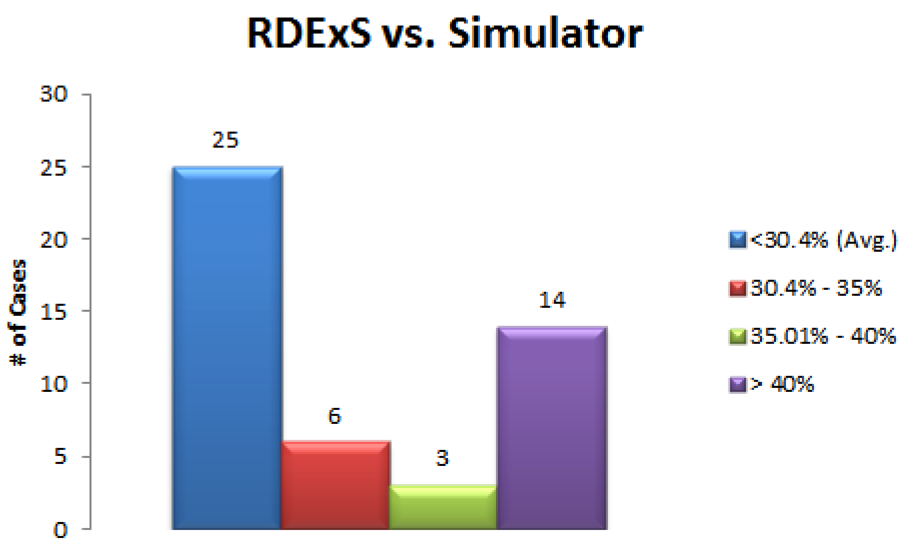


Fig. 6.15: RDExS vs. Simulator 48 Cases Distribution with Respect to Their Ranges of error Implemented to VSPGR.

6.4.1.1 Crosschecking the REExS with the Numerical Simulator

As discussed earlier, though the REExS resulted in high discrepancies when comparing reservoir properties predicted against targeted, it is yet not indicative enough of the robustness of the system in terms of pattern recognition. Therefore the closed loop approach illustrated in **Figure 6.16** was implemented for crosschecking.

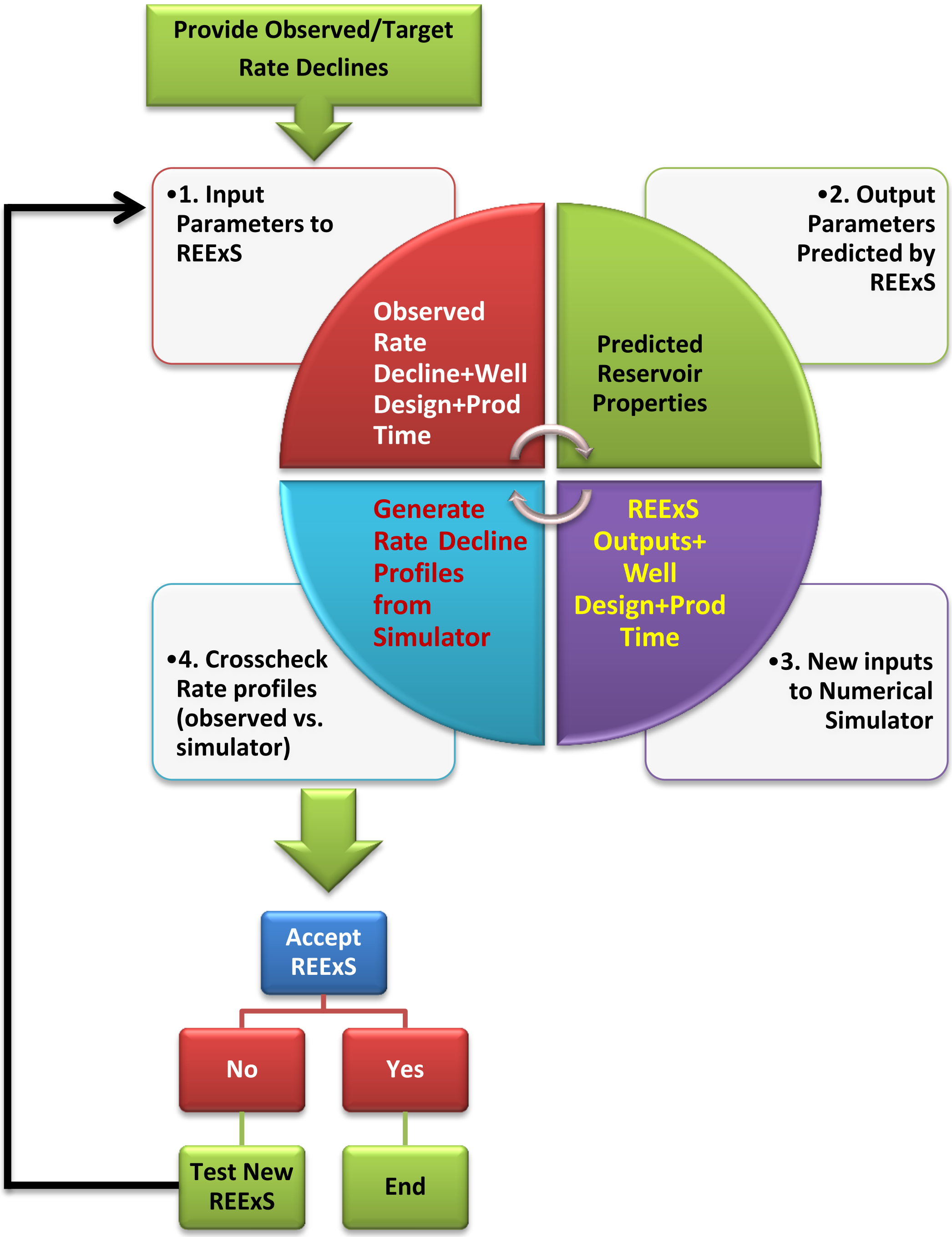


Fig. 6.16: Crosschecking Process for REExS Using the Numerical Simulator.

The 48 new data sets generated for directly testing REExS & RDExS were used again for indirect testing of REExS. The numerical simulator was applied to generate the corresponding rate decline profiles, referred to as target or observed, for each of the 48 reservoirs and their multi-laterals. Then the rate profiles with their respective multi-lateral well designs and production times were inputs to the REExS. The REExS generated its reservoir properties estimations for each of the 48 cases. Even though these properties were different from the original set used in the numerical simulator to produce the target rate declines yet it is not an indicator of whether these new properties would result in similar performances or not. Therefore the REExS predicted reservoir properties combined with their respective well designs and production periods were fed to the numerical simulator to generate their rate decline profiles, referred to as simulator. An overall average error of ~34.6% was measured when comparing both rate profiles, simulator vs. observed, for the 48 cases. The distribution of the cases with respect to their average error ranges are shown in **Figure 6.17**. However it's worth noting that 29 cases had an average error of only ~20% whereas the remaining 19 cases had an average error of ~57%.

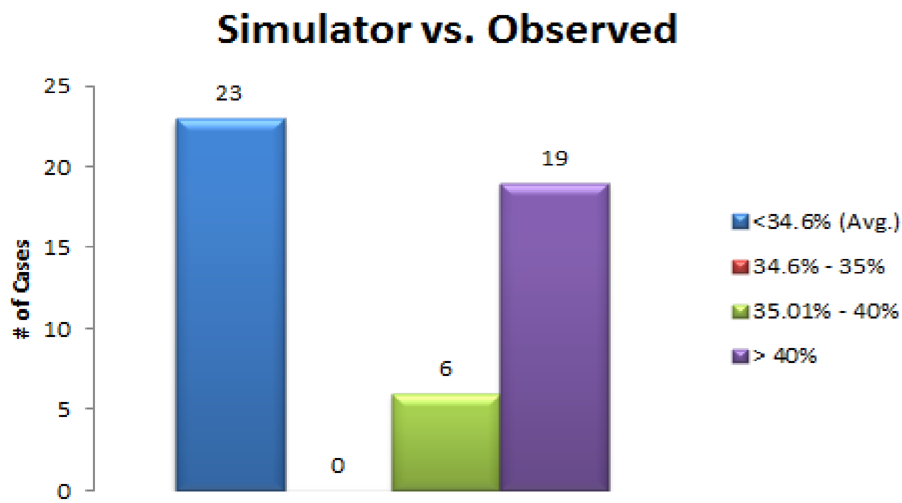


Fig. 6.17: Cases Distribution with Respect to their Ranges of Error when Comparing Observed Rates to Simulator Rates Using REExS Predictions Implemented to VSPGR.

6.4.1.2 Crosschecking REExS using RDExS

Here the REExS predicted reservoir properties were combined with their respective multi-lateral well design parameters and production times and fed to RDExS to predict their rate decline profiles, referred to as RDExS. Again this is a closed loop approach as demonstrated in **Figure 6.18**. By performing this cross-examination the RDExS robustness is crosschecked as well, since while confirming that the REExS estimated reservoir properties will result in a rate profile similar to what was observed, i.e. RDExS vs. Observed, in the same time the RDExS will be compared to the simulator results obtained from the previous section when using the numerical simulator, i.e. Observed vs. Simulator.

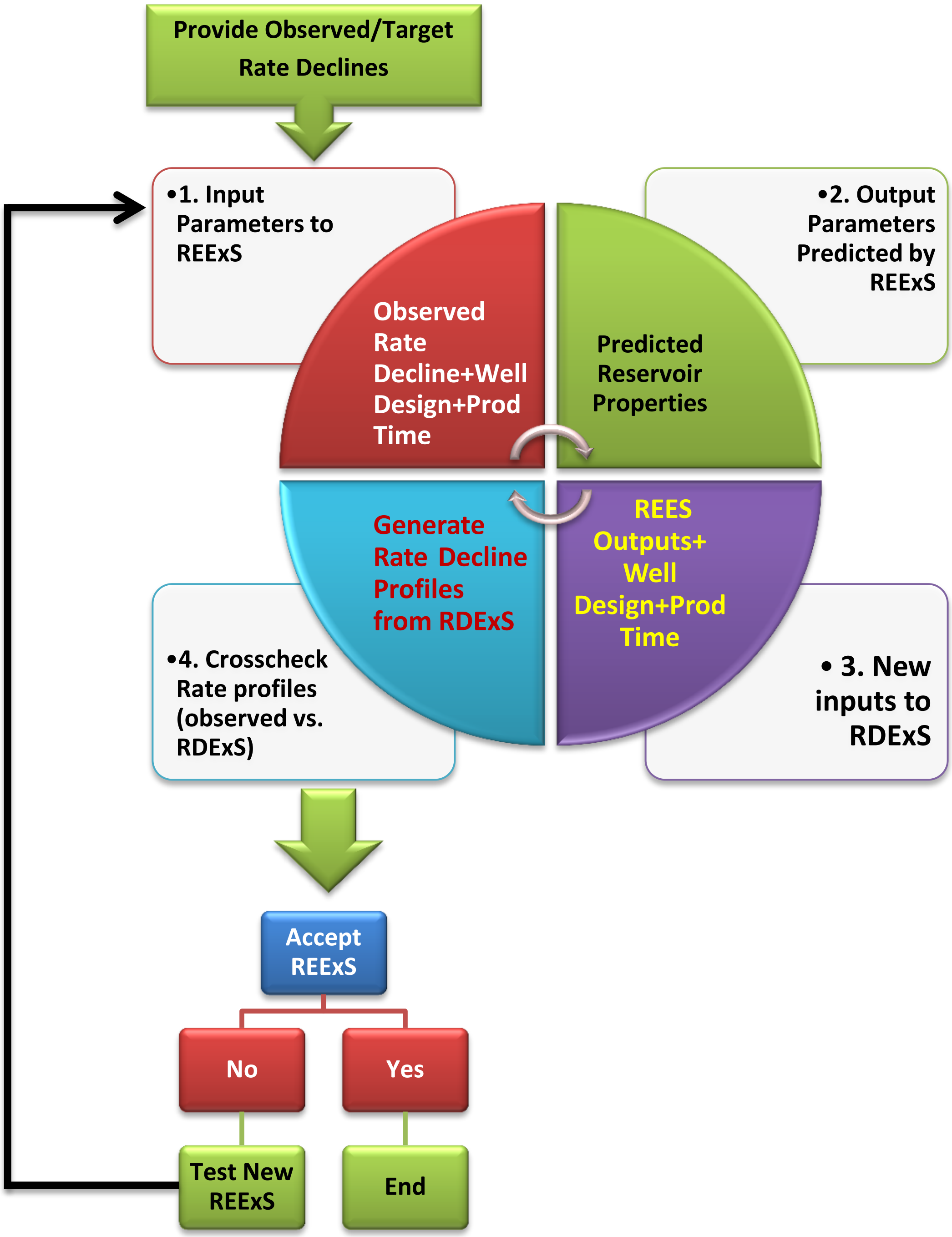


Fig. 6.18: Crosschecking Process for REExS Using RDExS.

Similar to the previous process when crosschecking with the numerical simulator, the so called observed rates and resepective well designs and production times of the 48 cases were inputs to REExS. Which in turn provides an estimation of the, aught to be corresponding, reservoir properties. Then to examine if this is true, these properties and the same set of well designs and production times were fed this time to the RDExS instead of the numerical simulator. The RDExS subsquently generated rate decline profiles for each of the 48 scenarios, referred to as RDExS. Hence these RDExS rate profiles were compared to the observed rate declines originally used to predict the reservoir properties. This resulted in an overall average error of ~48.4% which was considered high, nevertheless the break down of the cases with respect to their ranges of error indicated that 26 cases were below an average error of ~29% whereas 22 cases had average errors above 55% as illustrated in **Figure 6.19**.

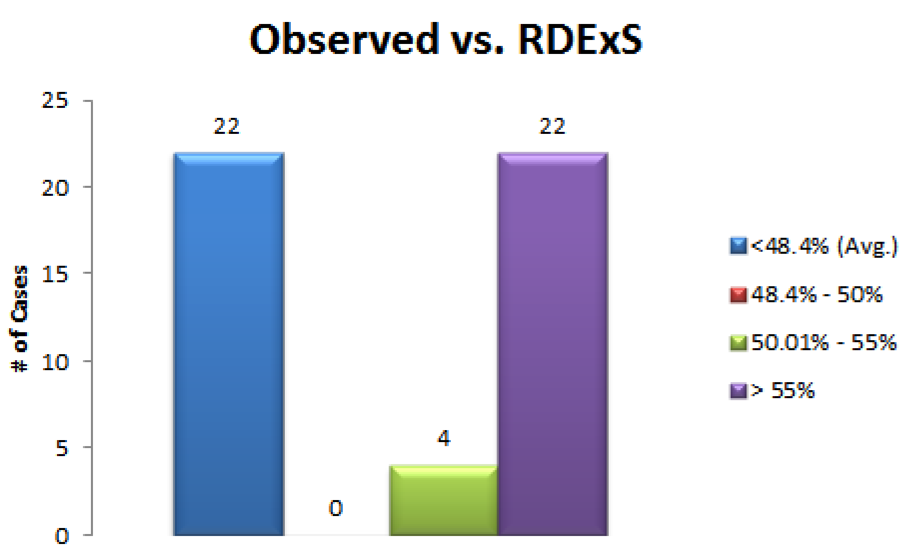


Fig. 6.19: Cases Distribution with Respect to their Ranges of Error when Comparing Observed Rates to RDExS Rates Using REExS Predictions Implemented to VSPGR.

In general both crosschecking methods show a good generalization and trend detection. The rate declines were broken into two groups. Group one, **Figure 6.20**, shows the tendency of the rate declines generated by both approaches to match the observed rate declines though the simulator rates were closer in most cases. The other group, **Figure 6.21**, highlights the cases that display a good agreement between the numerical simulator predictions and the RDExS rates. Eventhough these results mildly agree with the observed rates yet they add confidence to the RDExS estimates since both tools, i.e. the simulator and the RDExS had the same inputs from the same source, the REExS predictions.

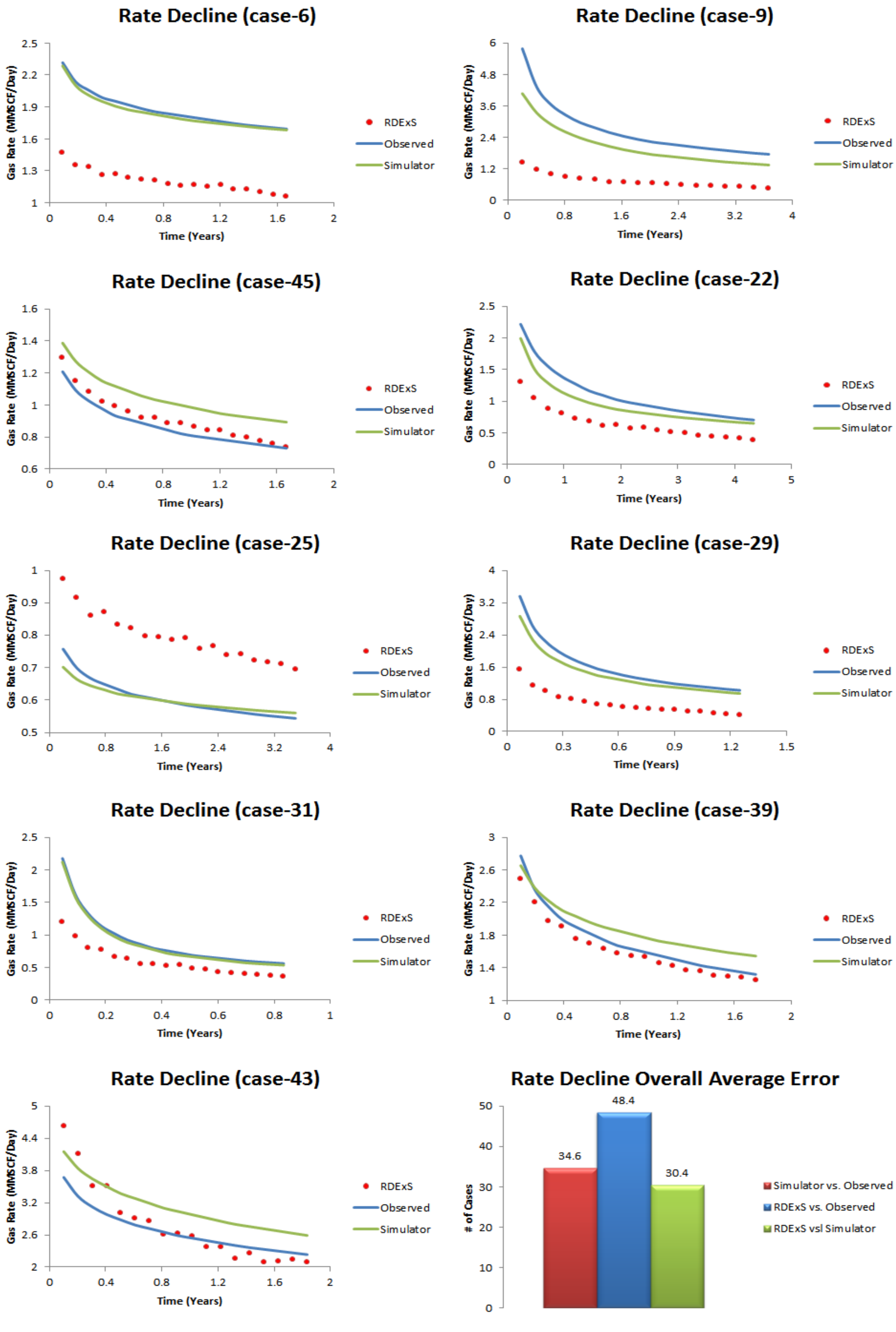


Fig. 6.20: Rate Declines Predicted by Both Crosschecking Methods Using the REExS Inputs Implemented to VSPGR.

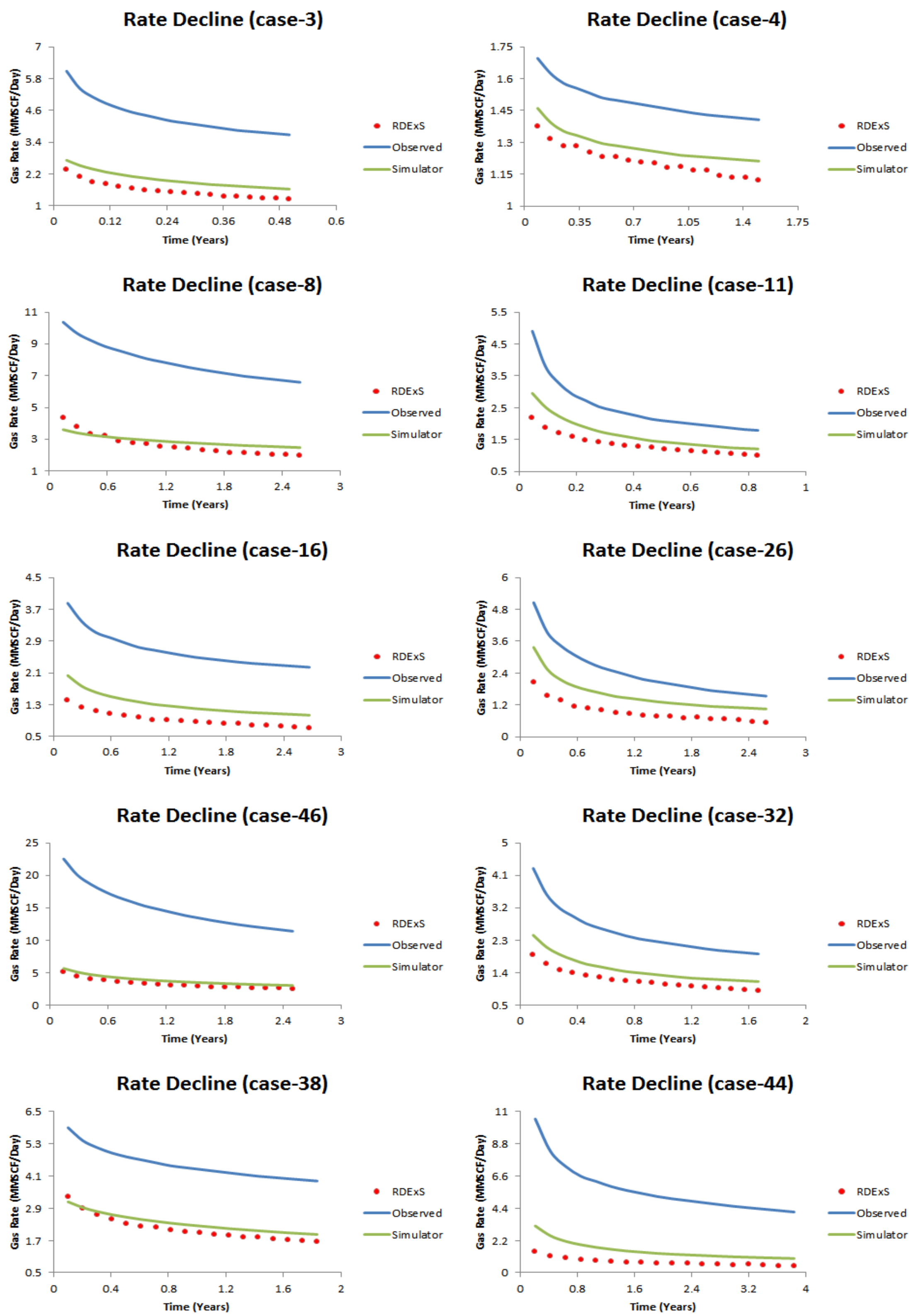


Fig. 6.21: Rate Declines Predicted by Both Crosschecking Methods Using the REExS Inputs.

Chapter 7 Developed Expert Systems for Multi-Phase Reservoirs with Bottom Water Drive

This chapter highlights the developed expert systems implemented to Multi-Phase Reservoirs with Bottom Water Drive (MPRBWD) with a variety of rock and fluid properties spanning slightly tight sands to conventional sands and with the flexibility of employing a multi-lateral well ranging from 2 to 5 laterals. Five distinct artificial neural networks are developed here, the Forecast Expert System (FExS) which predicts the cumulative % recoveries, however with added features that allow for more customization and flexibility such as the period desired to run the forecast for, and the initial maximum oil rate desired to produce at. The Multi-Lateral Well Design Advisory System (MLWDAS) also developed with the capability of specifying the initial maximum oil rate and time for which the target performance is covering. The Reservoir Evaluation Expert System (REExS) that partially characterizes the reservoir by predicting the permeability values in the normal and both lateral directions, the porosity, the reservoir thickness and the drainage area, however here with the inputs being the cumulative fluid production rather than rate decline since the subject reservoirs are multi-phase with the primary hydrocarbon production is oil in addition to the well configuration in place, other reservoir properties and the production duration. The Cumulative Fluid Production Expert System, called CFPExS for short, basically the inverse solution of REExS, to allow for a 360° approach in order to crosscheck the REExS results in case of the absence or unavailability of a numerical simulator, which can be used to reproduce the observed cumulative fluid production using the combination of properties predicted by REExS and the existing well design. The fifth one is another forecasting tool however with the capability of predicting the cumulative oil and gas productions, for how long is the plateau and when is the abandonment times for a given initial maximum oil rate and a set of reservoir and well design parameters, which as termed Cumulative-Abandonment-Plateau-Time-Expert-System, and referred to as CAPTExS for short.

7.1 Definition of Parameters

The parameters of **Table 6.1** is modified to include the added parameters and modified ranges for existing properties normally common for multi-phase reservoirs with bottom water drive. **Table 7.1** lists the entire reservoir, operating and well parameters definitions, units and ranges. A total of 2000 new cases are generated to populate the data base used for developing the expert systems described in this chapter.

Table 7.1: Reservoir, Well Design and Operating Parameters and Their Ranges

Category	Parameter	Abbreviation/Symbol	Unit/Rep	Min	Max
Reservoir	Vertical Permeability	k_v	md	0.1	50
Reservoir	Lateral Permeability in the ith direction	k_i	md	1.0	500
Reservoir	Lateral Permeability in the jth direction	k_j	md	1.0	500
Reservoir	Porosity	Φ	fraction	0.05	0.45
Reservoir	Total Reservoir Thickness	H	ft	10	250
Reservoir	Drainage Area	D_A	acres	100	500
Reservoir	Gas Density	ρ_g	lb/ft^3	0.04	0.08
Reservoir	Oil Density	ρ_o	lb/ft^3	50	58
Reservoir	Initial Pressure	P_i	psi	1500	5300
Reservoir	Bubble Point Pressure	P_b	psi	1500	5300
Reservoir	Depth to Top of Reservoir from Surface	DTOP	ft	3000	10000
Operate	Maximum Initial Daily Oil Rate	Q_o	STB/D	2000	10000
Operate	Minimum Flowing Bottom Pressure	P_{wf}	psi	14.7	14.7
Monitor	Minimum Daily Oil Rate	Q_o	STB/D	50	50

Cont. Table 7.1

Category	Parameter	Abbreviation/Symbol	Unit/Rep	Min	Max
Monitor	Maximum Gas Oil Ratio	GOR	SCF/STB	4000	4000
Monitor	Maximum Water Cut	wc	%	99	99
Well	Total # of Laterals	ML	# of laterals	2	5
Well	Location of 1st lateral	L_1	layer #	1	10
Well	Location of 2nd lateral	L_2	layer #	1	10
Well	Location of 3rd lateral	L_3	layer #	1	10
Well	Location of 4th lateral	L_4	layer #	1	10
Well	Location of 5th lateral	L_5	layer #	1	10
Well	Length of 1st lateral	L_{n1}	ft/cell #	200/3	1800/12
Well	Length of 2nd lateral	L_{n2}	ft/cell #	200/3	1800/12
Well	Length of 3rd lateral	L_{n3}	ft/cell #	200/3	1800/12
Well	Length of 4th lateral	L_{n4}	ft/cell #	200/3	1800/12
Well	Length of 5th lateral	L_{n5}	ft/cell #	200/3	1800/12
Well	Horizontal separation between heels	H_s	ft/cell #	1.0e-08	200/3
Well	Phase angle between laterals	θ	degrees	45	180

7.2 Forecast Expert System (FExS) Development for Multi-Phase Reservoirs with Bottom Water Drive (MPRBWD)

This system is similar in concept to the forecast system developed for implementation in the Volumetric Single Phase Gas Reservoirs (VSPGR), described in section 6.1.2., however with added parameters and features that help increase the accuracy and allows more flexibility for customizing and testing different scenarios. In this set up six additional parameters are introduced to the network input. The top depth of the reservoir from surface, the oil density, the original oil in place, the bubble point pressure, the initial maximum oil rate and the period the user wants to forecast for ranging from a year to 60 years. The time and initial oil rate added features give the user the flexibility to examine variable performances for a unique combination of reservoir properties and well design parameters. Whereas the top depth and original oil in place help increase the accuracy of the network by increasing the uniqueness of each case. **Figure 7.1** illustrates the structured ANN for this system consisting of 27 inputs 5 hidden layers with 70, 65, 60, 50 and 30 neurons respectively and 18 outputs. The objective of developing this system is to deliver an acceptable performance forecast in terms of cumulative % recoveries at 18 different time steps covering the period provided by the user for a subject reservoir and its well design parameters.

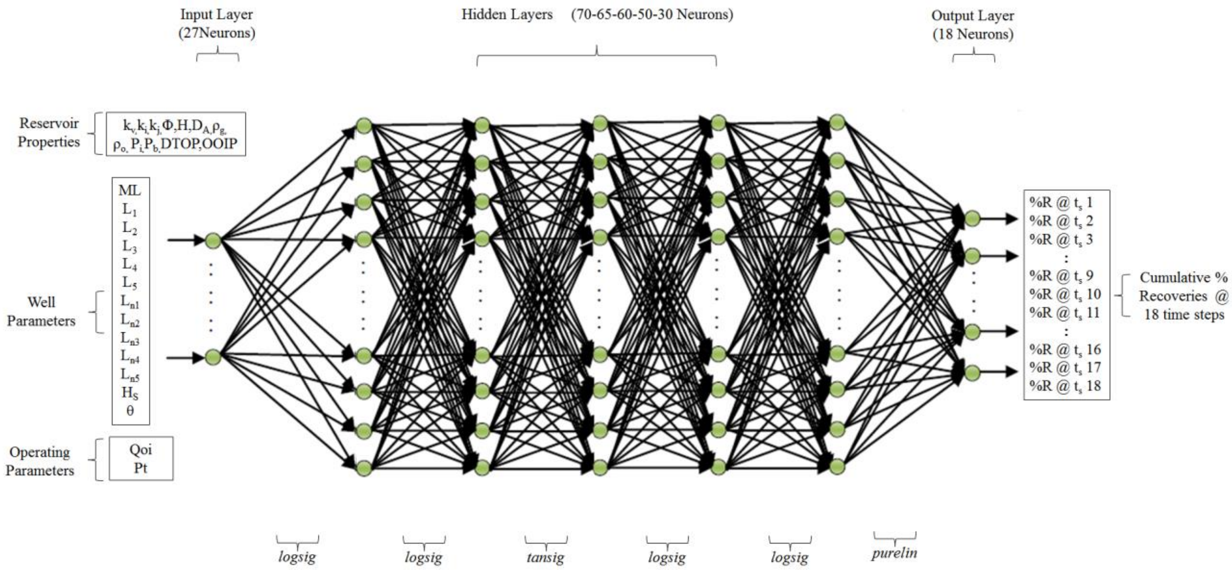


Fig. 7.1: FExS Implemented to (MPRBWD).

7.2.1 Testing Forecast Expert System (FExS) Applied to Multi-Phase Reservoirs with Bottom Water Drive (MPRBWD)

Towards reaching the above network 1800 data sets are randomly divided between training, validating and testing with 85%, 10% and 5% respectively. The average error of the 90 tested cases was 13.17%. However it's worth noting that 64 out of the 90 tested cases had errors less than 6%. **Figure 7.2** details the breakdown of the number of cases with respect to their ranges of error and **Figure 7.3** shows the comparison plots between targeted cumulative % recoveries and predicted by FExS for 8 cases where the case numbers reflect the actual test indices out of the 1800 data sets.

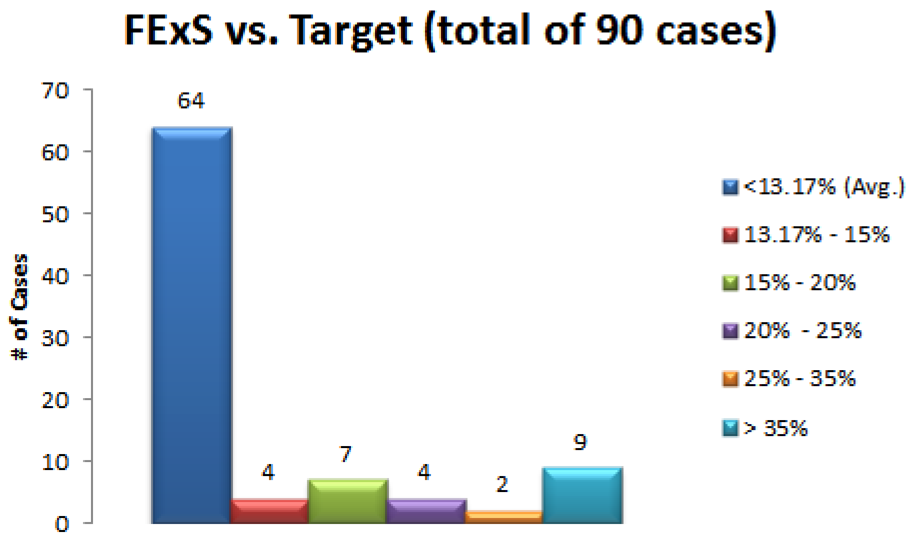


Fig. 7.2: FExS Results and Their Respective Errors Implemented to MPRBWD.

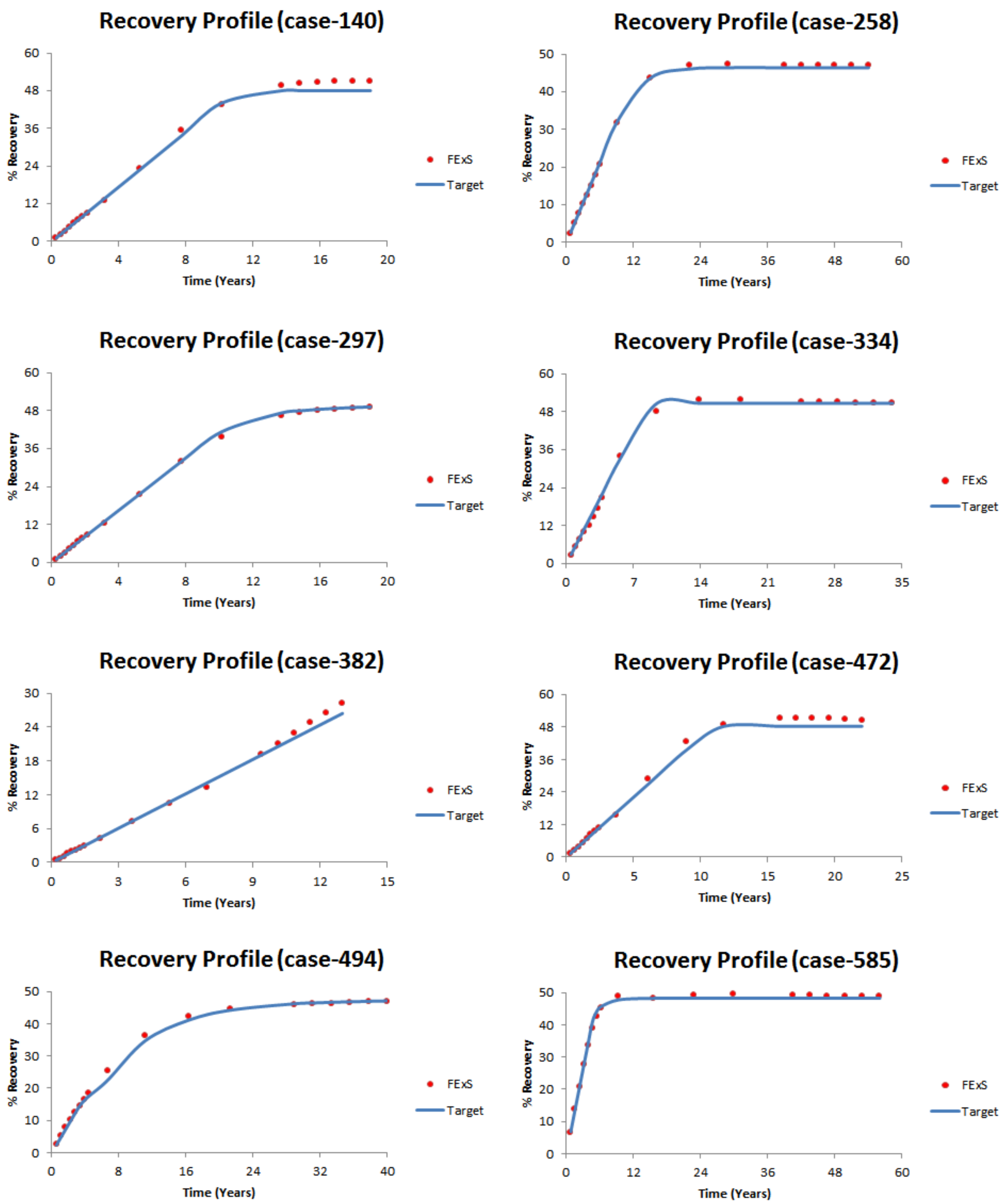


Fig. 7.3: Comparison Plots Between the Recovery Profiles Predicted by FExS and the Simulator (Target) Implemented to MPRBWD.

7.3 Multi-Lateral Well Design Advisory System (MLWDAS) Development for Multi-Phase Reservoirs with Bottom Water Drive (MPRBWD)

Similar to its development in section 6.2 for the Volumetric Single Phase Gas Reservoirs (VSPGR) where the multi-lateral well design parameters along with its assigned drainage area are switched to the output layer and the target % recoveries are combined with the reservoir properties and operating parameters at the input layer. From previous experience gained in developments of this particular problem, the success criteria here is measured by comparing the reservoir performance resulted by completing the target reservoir with the predicted well design parameters to the target reservoir performance of the same reservoir provided as input to the network. This is done by implementing one of the closed loop approach concepts outlined in sections 6.2.1 and 6.2.2 and summarized in **Figures 6.5** and **6.7** for using a numerical simulator or the FExS, developed for MPRBWD in this case, respectively.

7.3.1 Multi-Lateral Well Design Advisory System (MLWDAS) ANN Architecture

The same data set, 1800 cases, used for developing FExS in this chapter are rearranged for training, validating and testing the ANN structures for developing the MLWDAS used for MPRBWD. The successful network is shown in **Figure 7.4**. It consists of two hidden layers with 40 and 35 neurons respectively, 31 input parameters grouped into sets of reservoir properties, target cumulative percent recoveries at 18 time steps over a specified period of time, and operating parameters. The output layer contains 14 neurons representing 13 multi-lateral well design parameters and the proposed drainage area. The developed network returned an overall absolute average error of 7 comparing between target and predicted well design parameters, however as mentioned before, the key performance indicator here for the success of the network is testing the performance of the predicted well design against the targeted performance using one of the closed loop approaches.

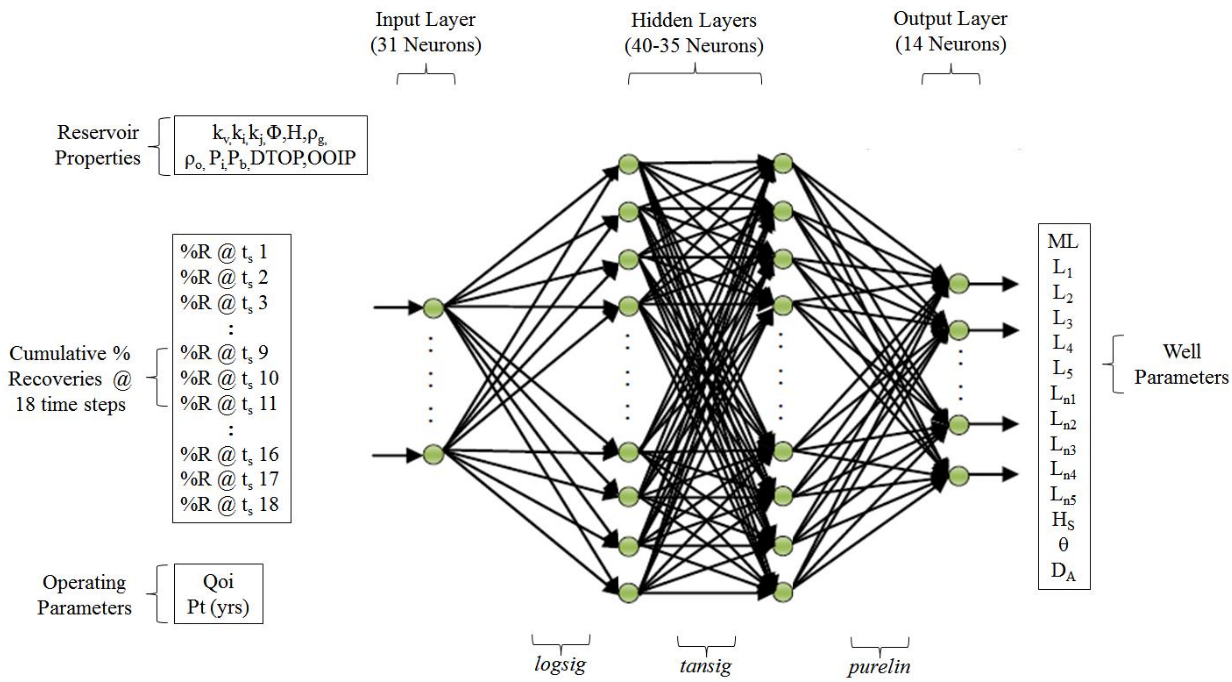


Fig. 7.4: MLWDAS Implemented to MPRBWD.

7.3.2 Crosschecking Multi-Lateral Well Design Advisory System (MLWDAS) with the Numerical Simulator

Eighty eight multi-lateral well design sets predicted by MLWDAS are tested using the numerical simulator by combining them with their corresponding reservoir properties and operating parameters to reproduce the cumulative recoveries and compare each to the target cumulative recovery. The crosschecking resulted in an overall average error of ~8.38% where 59 cases had an overall average error of less than 4.2% as displayed in **Figure 7.5**. Eight cases are shown in **Figure 7.6** comparing target versus simulator cumulative recoveries.

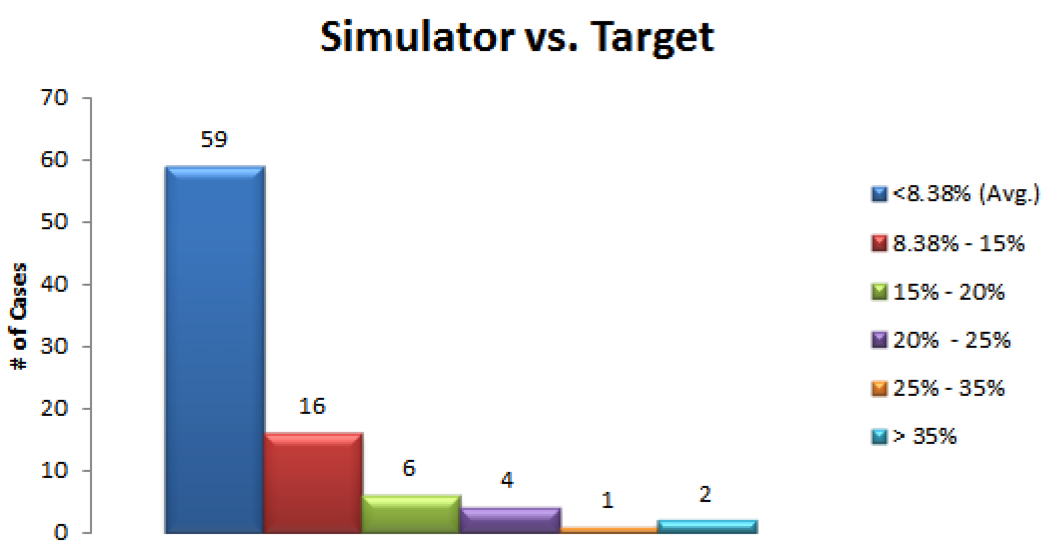


Fig. 7.5: Target vs. Simulator of 88 Cases According to their Ranges of Error Implemented to MPRBWD.

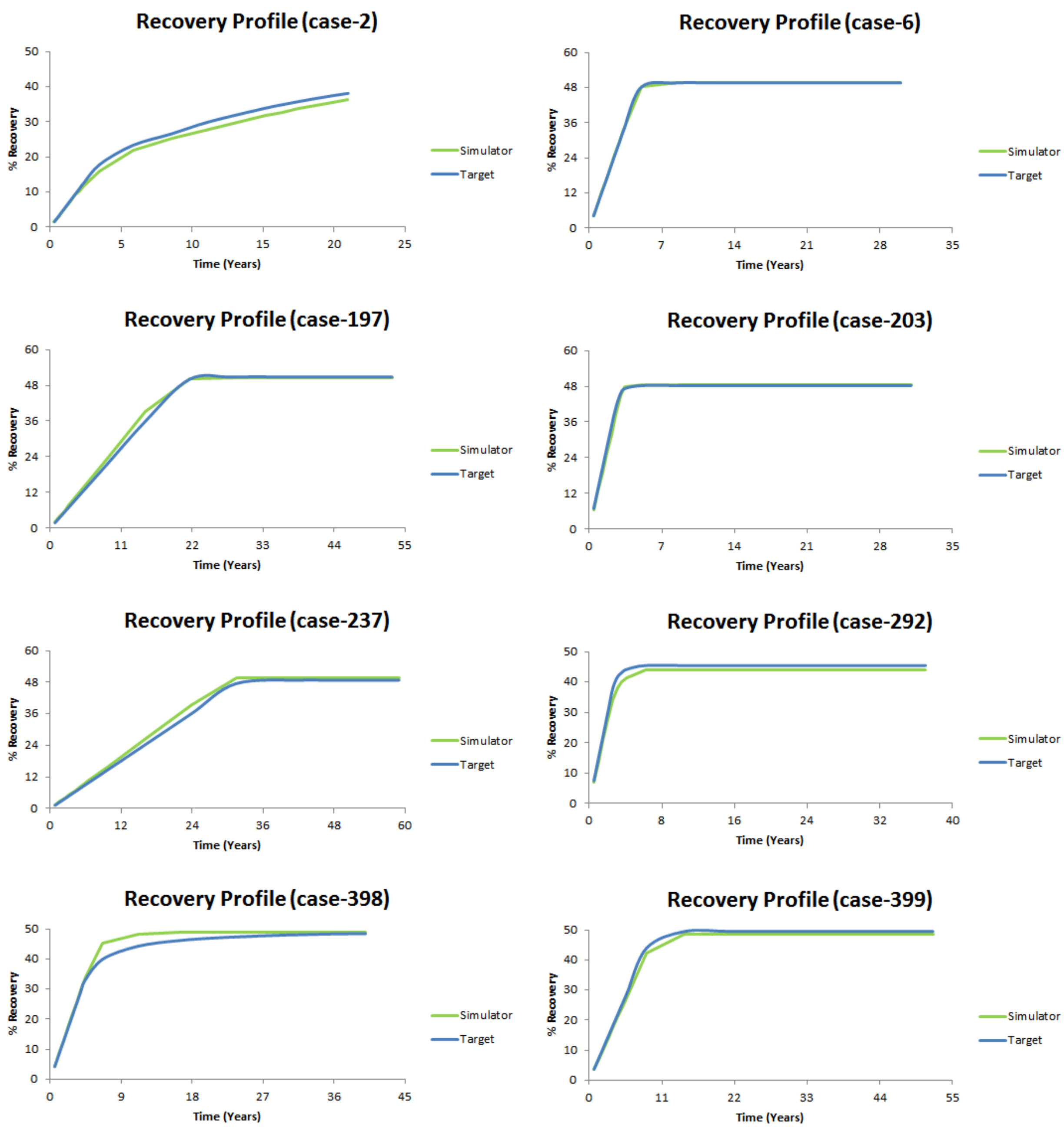


Fig. 7.6: Comparison Plots Between Target Recovery Profiles and Reproduced Profiles using the Numerical Simulator Implemented to MPRBWD.

7.3.3 Crosschecking Multi-Lateral Well Design Advisory System (MLWDAS) using the Forecast Expert System (FExS)

The same 88 multi-lateral well design sets predicted by MLWDAS are tested using this time FExS by combining them with their corresponding reservoir properties and operating parameters and provide them as inputs to FExS to reproduce the cumulative recoveries and compare each to its target cumulative recovery. The crosschecking resulted in an overall average error of ~12.23% where 64 cases had an overall average error of less than 5.6% as displayed in **Figure 7.7**. Eight cases are shown in **Figure 7.8** comparing target versus FExS predicted cumulative recoveries.

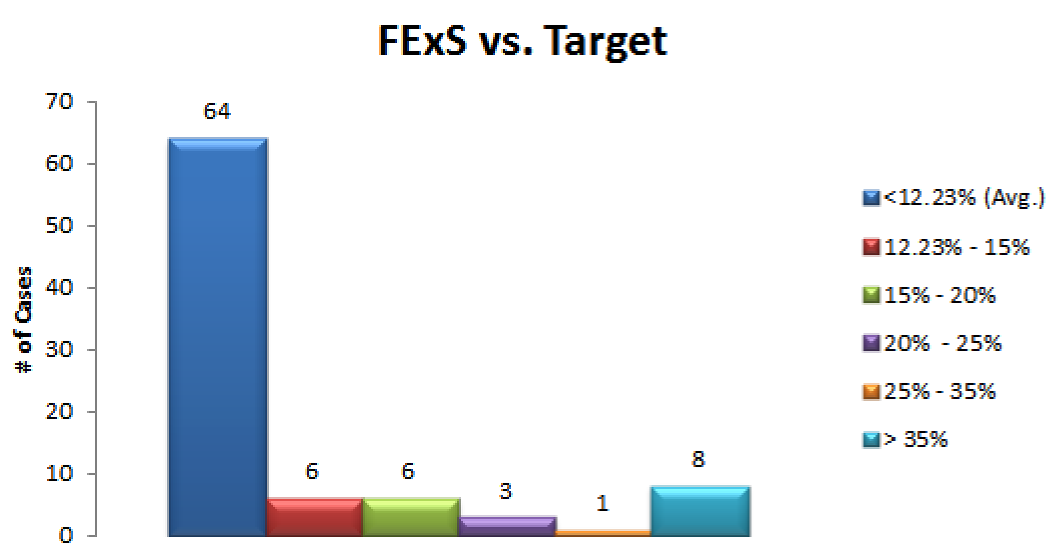


Fig. 7.7: Target vs. FExS of 88 Cases According to their Ranges of Error Implemented to MPRBWD.

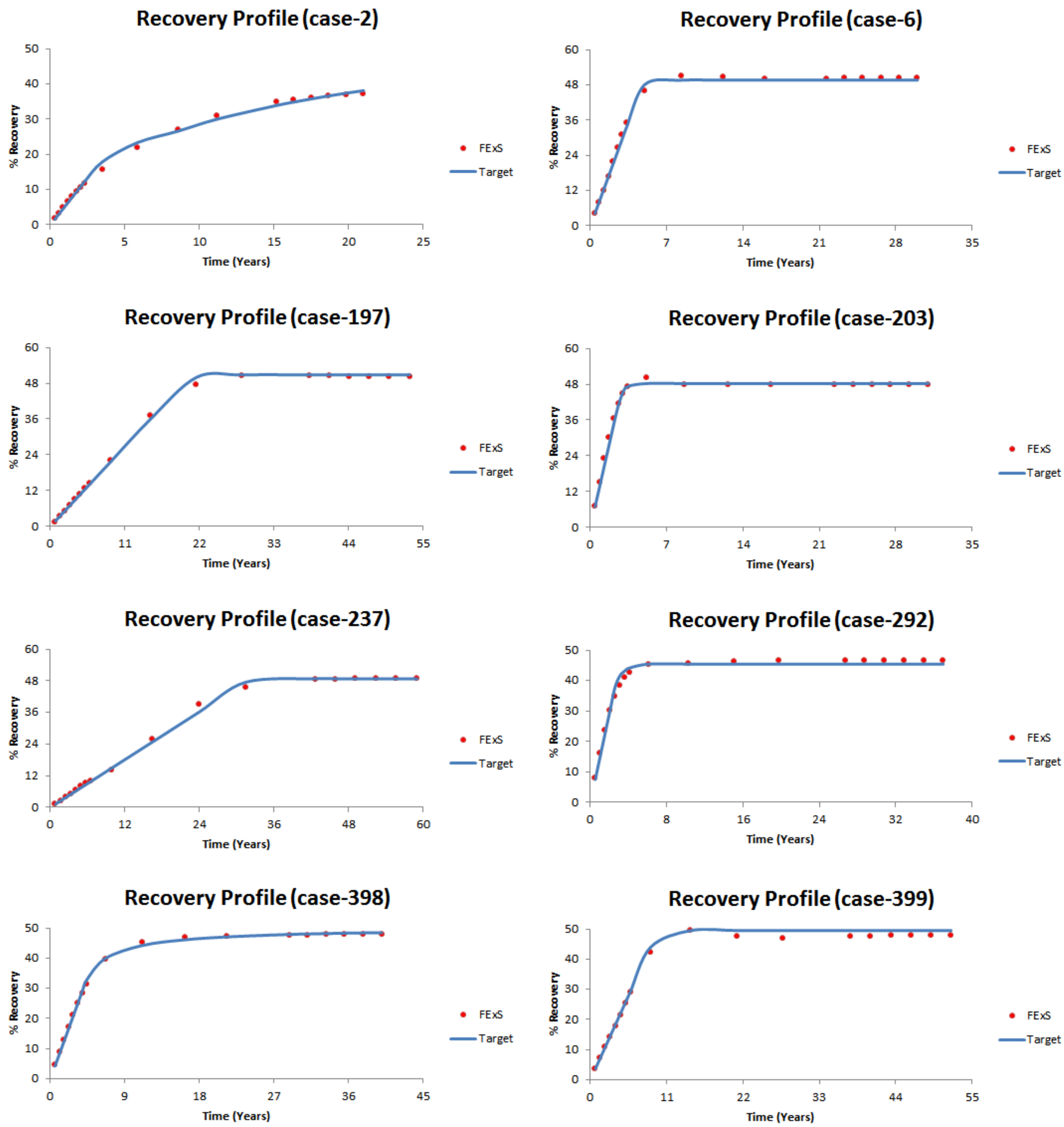


Fig. 7.8: Comparison Plots Between Target Recovery Profiles and Reproduced Profiles using FExS Implemented to MPRBWD.

7.3.4 Comparing all Target, Simulator and Forecast Expert System (FExS) Profiles

Since FExS was used to reproduce the 88 cumulative recoveries it is another opportunity to examine the robustness of FExS again by comparing it the results obtained by the simulator with respect to the original targets. **Figure 7.9** summarizes the overall average errors obtained from the previous crosschecking methods in addition to the overall average error between FExS and the numerical simulator with respect to the targets. **Figure 7.10** shows the comparison plots of the cumulative recoveries obtained from all methods and indicates an excellent match between all of them hence increasing confidence in FExS.

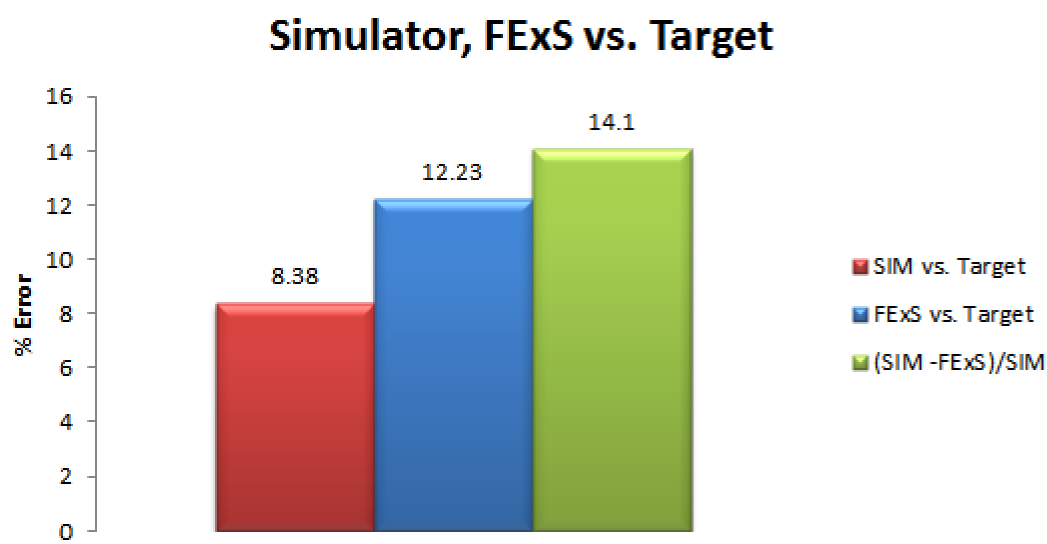


Fig. 7.9: The Overall Average Errors Between All Methods Implemented to MPRBWD.

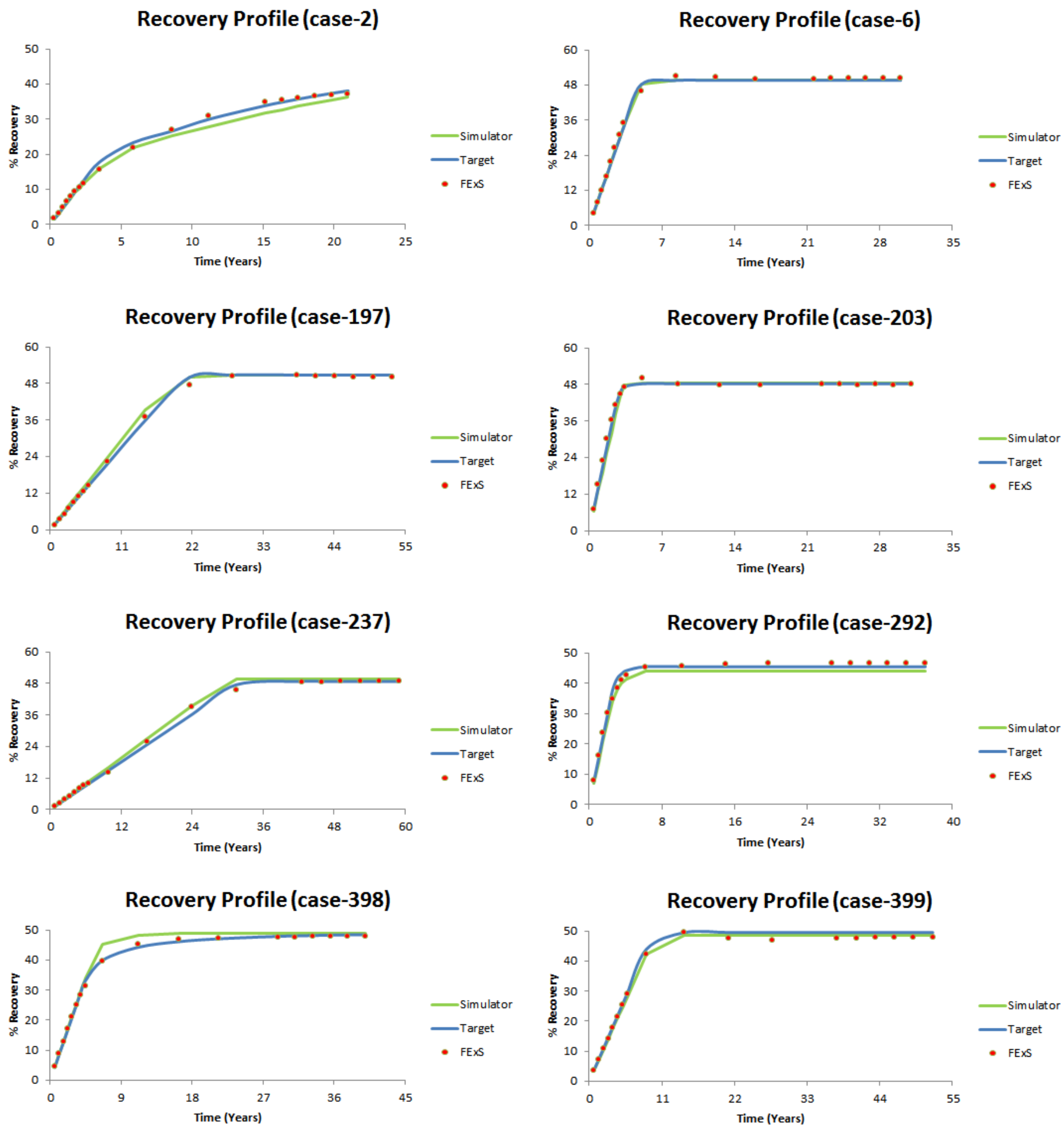


Fig. 7.10: Comparison Plots of Recovery Profiles Obtained by All Methods Implemented to MPRBWD.

7.4 Reservoir Evaluation Expert System (REExS) Development for Multi-Phase Reservoirs with Bottom Water Drive (MPRBWD)

The objective of developing REExS is to deliver at the very least a first educated guess of some of the critical reservoir properties that can guide history matching exercises or help gauge decisions and designs pertaining to infill drilling or field operations of adjacent prospects. However similar to the development in the VSPGR, the network's success is assessed by applying the closed loop approach first.

7.4.1 Reservoir Evaluation Expert System (REExS) ANN Architecture for Multi-Phase Reservoirs with Bottom Water Drive (MPRBWD)

The data set used for developing REExS contained 1700 cases. The input parameters consist of 4 reservoir properties which are the oil and gas densities and initial and bubble point pressures, 13 multi-lateral well design parameters, the maximum initial oil rate and months of production ranging from 1- 60 months as operating parameters, and the cumulative fluid production at 18 time steps over the production duration specified, adding up to a total of 37 inputs. The network is to predict 6 reservoir parameters which are the normal and two lateral permeability values, the porosity, the reservoir thickness and the drainage area. The developed ANN is shown in **Figure 7.11** and designed with 4 hidden layers with 70, 65, 60 and 50 neurons respectively.

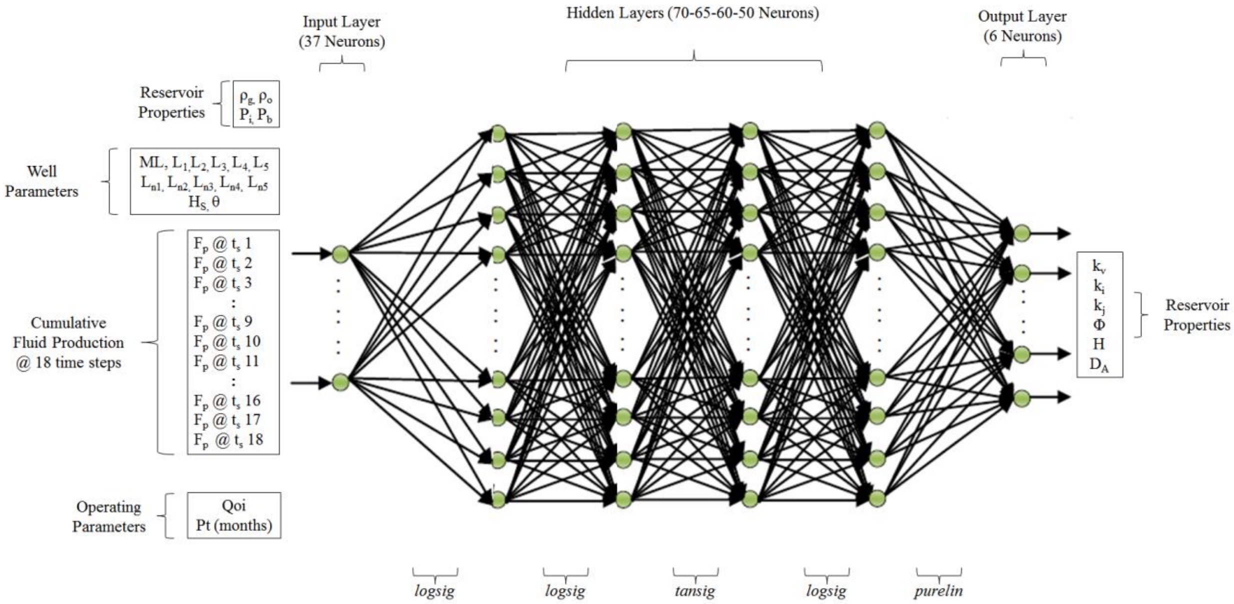


Fig. 7.11: REExS Implemented to MPRBWD.

7.4.2 Crosschecking Reservoir Evaluation Expert System (REExS) with the Numerical Simulator

The REExS test set contained 85 cases in each case predicting 6 reservoir properties as mentioned previously. To check the validity of the network, the combined reservoir properties predicted are grouped with their corresponding multi-lateral well design configurations, maximum initial oil rate, duration and the other reservoir parameters to form the data file used to run the simulator. The objective is now to crosscheck the reproduced cumulative fluid productions with the target fluid productions used as inputs to the REExS. The reproduced cumulative fluid productions were in good agreement with the targets supported by an overall average error of 13.37%. Furthermore 61 cases out of the total 85 have an overall average error of 3.27%. The breakdowns of the tested cases with respect to their errors are shown in **Figure 7.12**. The comparison plots of 8 cases are also displayed in **Figure 7.13**.

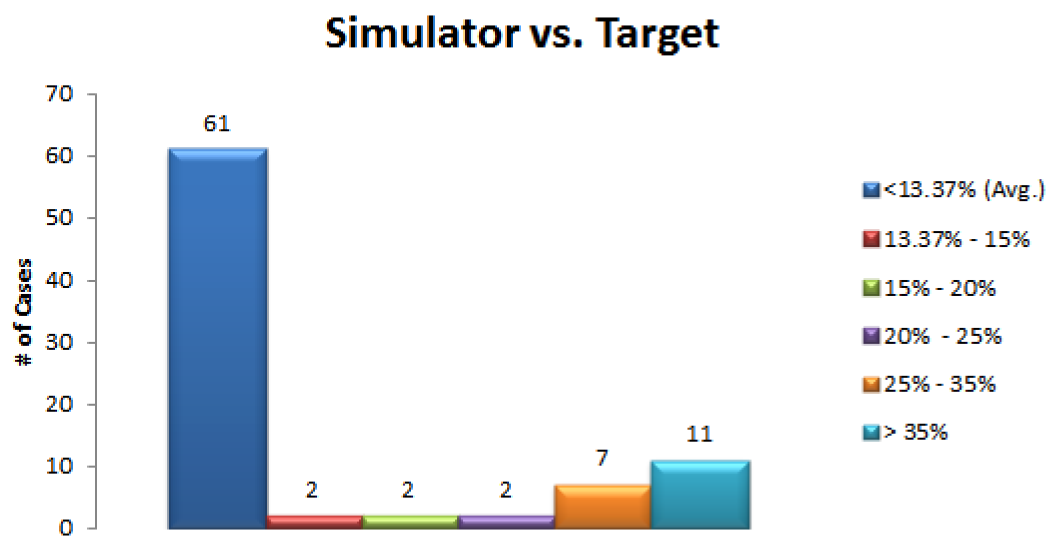


Fig. 7.12: Target vs. Simulator of 85 Cases According to their Ranges of Error Implemented to MPRBWD.

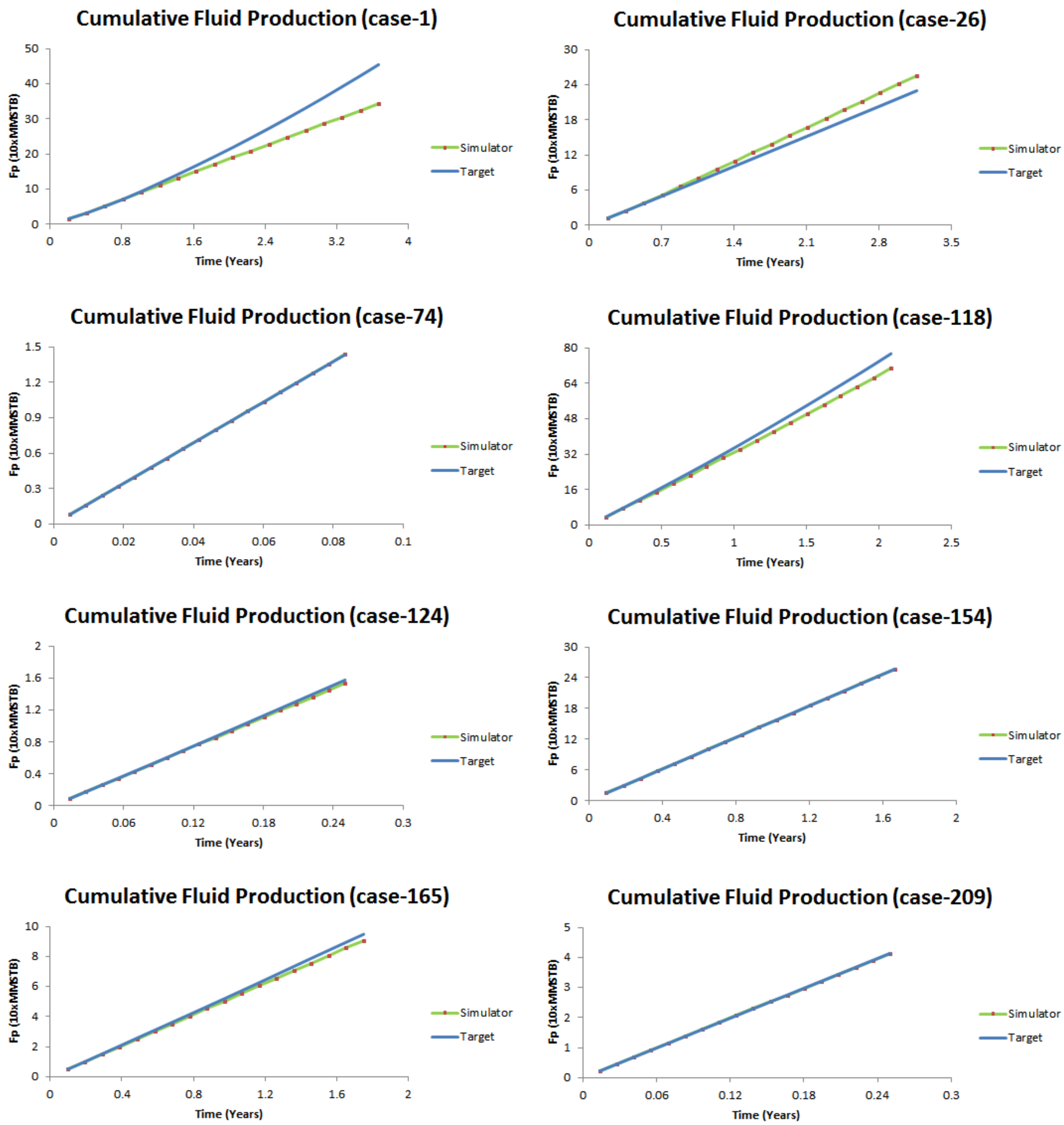


Fig. 7.13: Comparison Plots Between Target Cumulative Fluid Production Profiles and Reproduced Profiles using Numerical Simulator using REExS Predicted Reservoir Properties Implemented to MPRBWD.

7.5 Cumulative Fluid Production Expert System (CFPExS) Development

The objective of developing this system is to serve as the forward-looking solution to the REExS to have a complete loop. In case of the unavailability of a numerical simulator the CFPExS can be used as a secondary tool to crosscheck the REExS predictions. The CFPExS task is to predict the cumulative fluid productions for a given set of reservoir properties, multi-lateral well design and operating parameters. The CFPExS is designed with a total of 25 inputs and delivers 18 outputs of cumulative fluid productions 18 time steps covering the duration specified at the input. The network illustrated in **Figure 7.14** consists of 5 hidden layers with 322, 123, 187, 449 and 213 neurons respectively. After 133 training attempts this network with an overall average error of 29.17% was the least error achieved. The testing set contained 89 cases where 34 of them had an average error less than 15% as illustrated in the breakdowns in **Figure 7.15**. In addition **Figure 7.16** shows the comparison plots of the cumulative fluid productions between targets and those predicted by CFPExS for 8 cases.

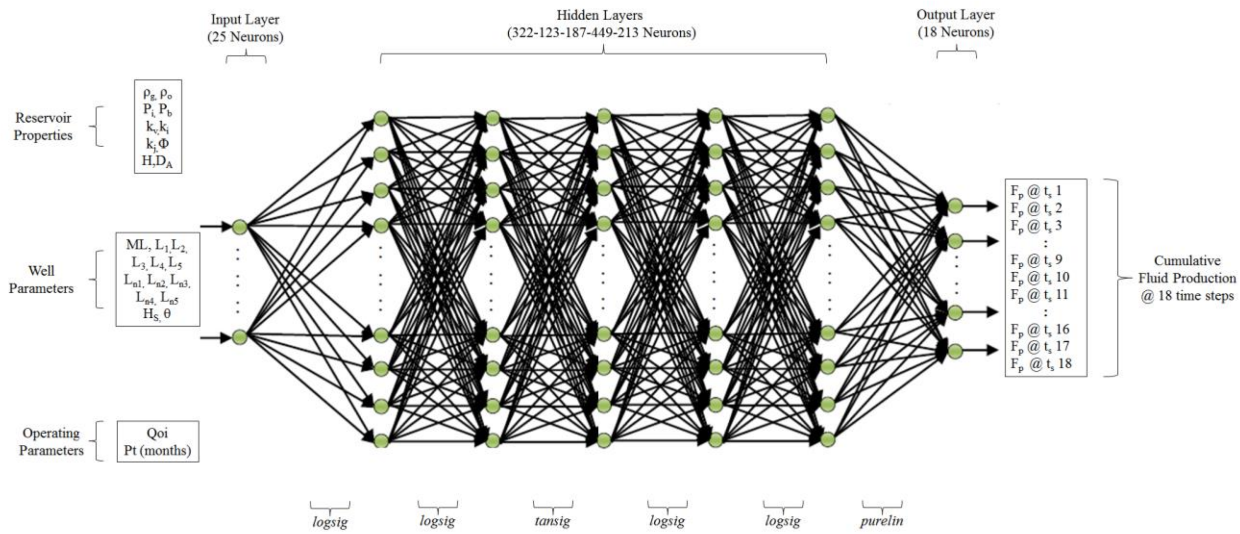


Fig. 7.14: CFPExS Implemented to (MPRBWD).

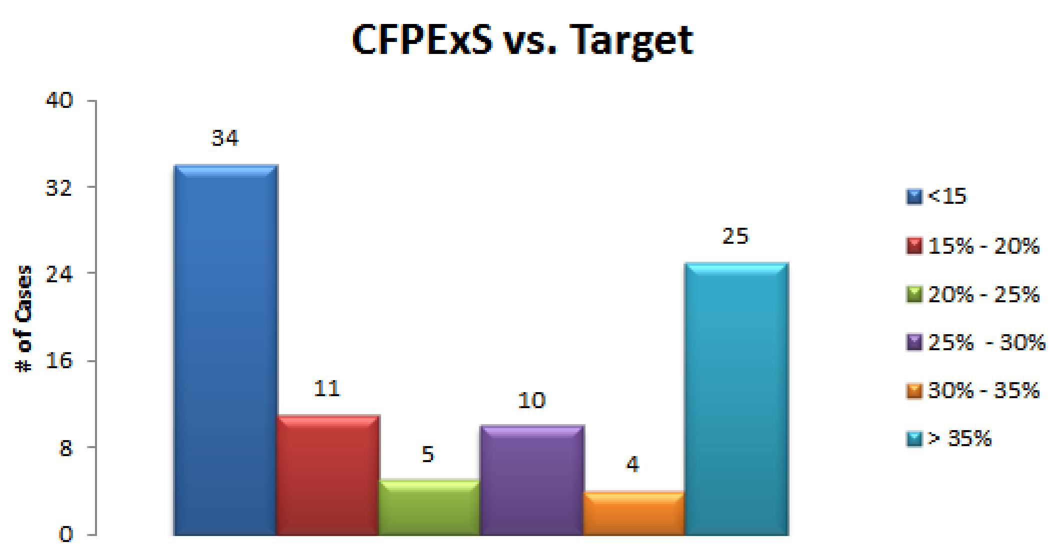


Fig. 7.15: Target vs. CFPExS of 89 Cases According to their Ranges of Error Implemented to MPRBWD.

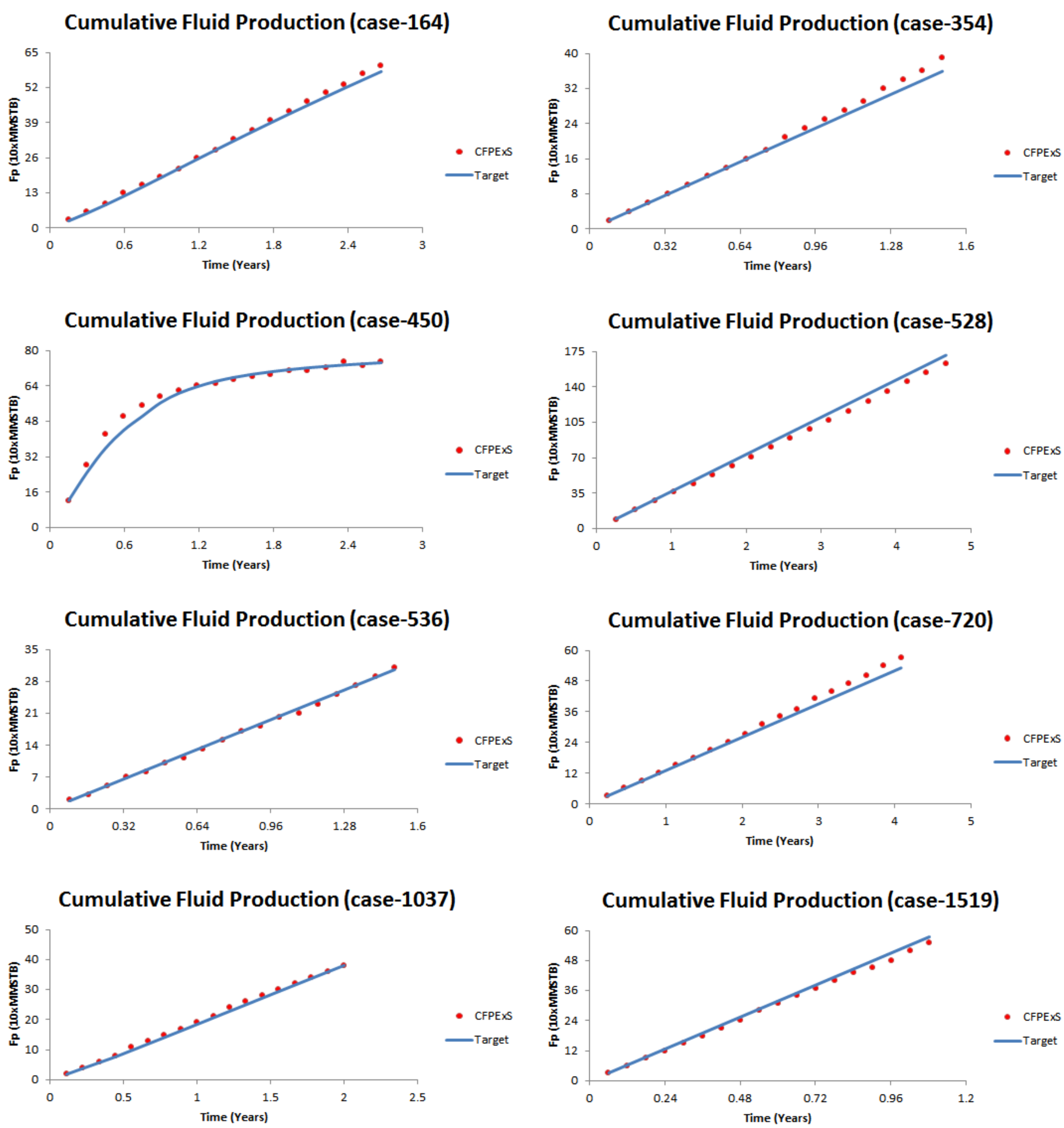


Fig. 7.16: Comparison Plots Between Target and CFPExS Cumulative Fluid Production Profiles Implemented to MPRBWD.

7.5.1 Crosschecking Reservoir Evaluation Expert System (REExS) using the Cumulative Fluid Production Expert System (CFPExS)

The outputs of REExS for the test set containing 85 cases are combined with their corresponding multi-lateral well design configurations, maximum initial oil rate, duration and the other reservoir parameters to form the input parameters to CFPExS. The objective is now to crosscheck the reproduced cumulative fluid productions with the target fluid productions used as inputs to the REExS. The reproduced cumulative fluid productions were in a fair agreement with the targets producing an overall average error of 34.7% however with 38 cases with errors less than 15%. The breakdowns of the tested cases with respect to their errors are shown in **Figure 7.17** and the comparison plots of the same 8 cases crosschecked with simulator as shown in **Figure 7.13** are plotted again however crosschecked with CFPExS as in **Figure 7.18**.

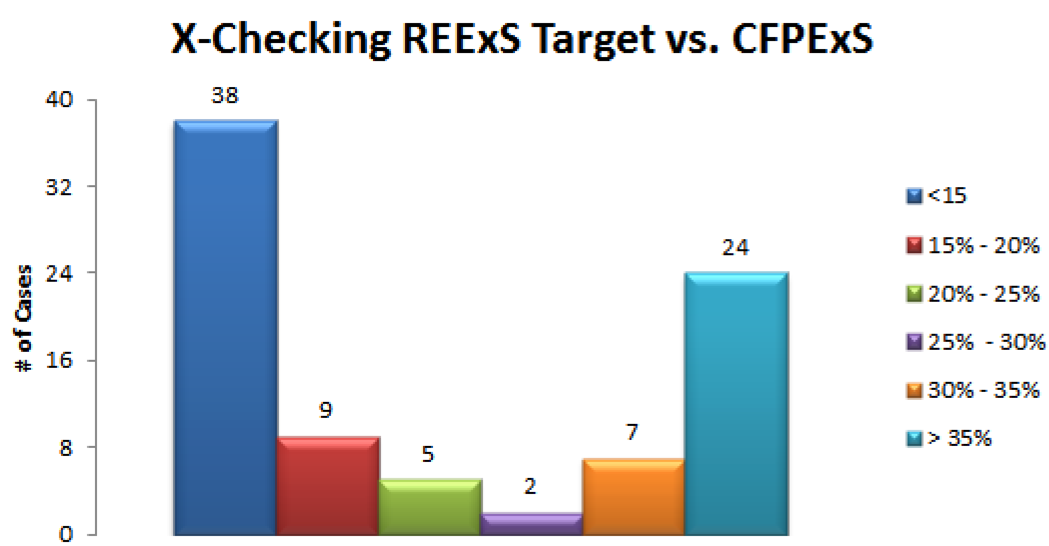


Fig. 7.17: Target vs. CFPExS of 85 Cases According to their Ranges of Error Implemented to MPRBWD.

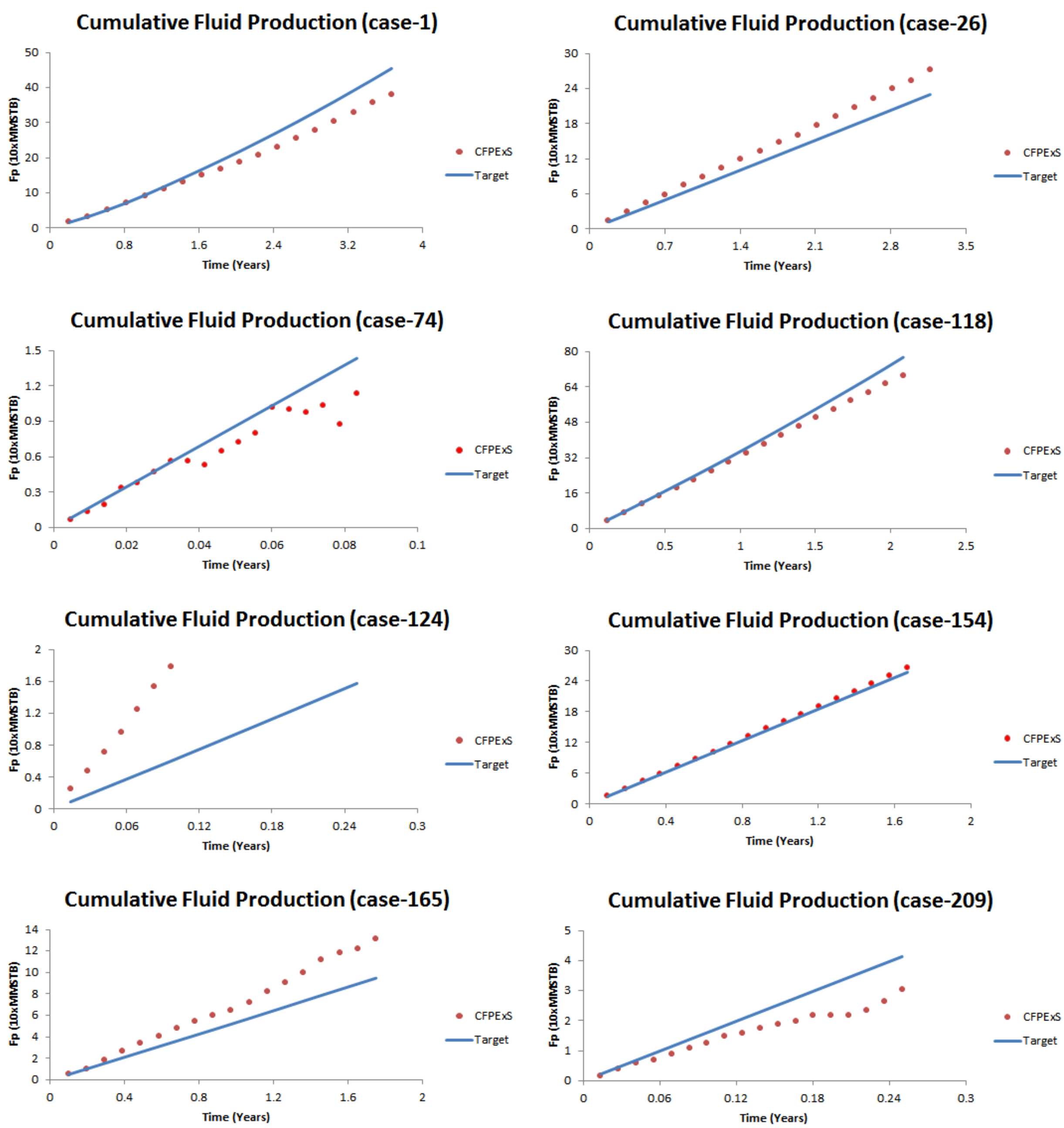


Fig. 7.18: Comparison Plots Between REExS Targets and CFPExS Cumulative Fluid Production Profiles Implemented to MPRBWD.

7.6 Cumulative, Abandonment and Plateau Times Expert System (CAPTExS) Development

This system generates 3 main categories, the cumulative productions of oil and gas, the duration of the plateau for a given maximum initial oil rate, and the abandonment time. This is tremendously valuable when performing quick economic analysis. It allows the user to modify parameters and examine what if scenarios. For example, explore different well designs and compare plateau times for different designs or vary initial oil rates for calculations of net present values. The network was trained with 1800 data sets each set with 25 input and 38 output parameters. The input consists of reservoir properties, multi-lateral well design parameters and the maximum initial oil rate as an operating parameter. The output contains 18 cumulative oil productions, 18 cumulative gas productions, the plateau time and the abandonment time. The successful ANN architecture is displayed in **Figure 7.19**.

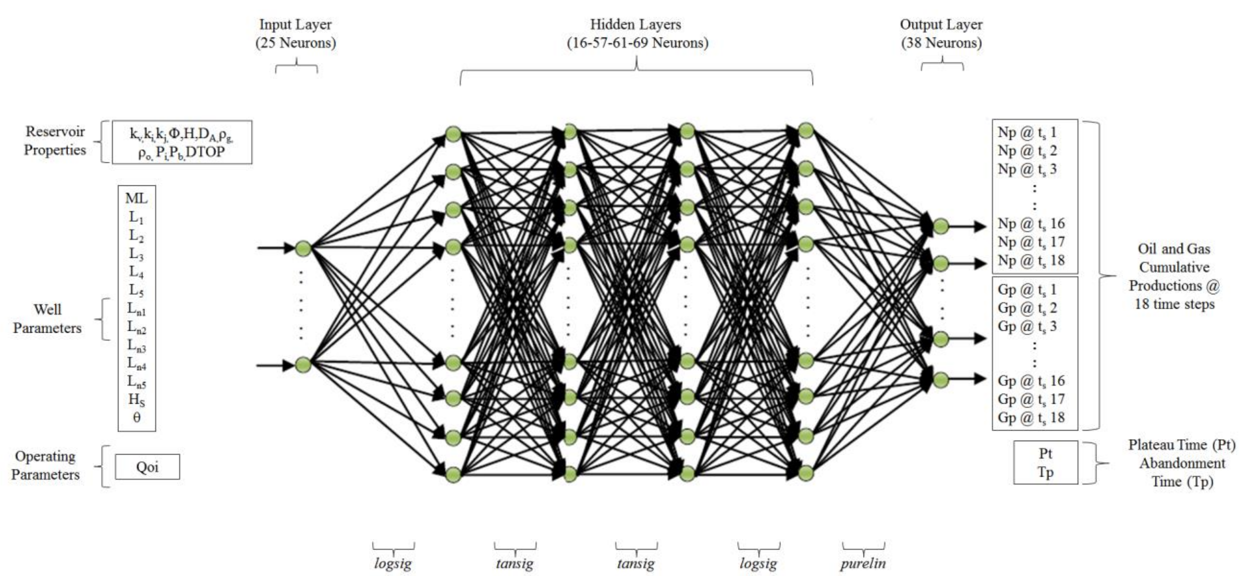


Fig. 7.19: CFPExS Implemented to (MPRBWD).

7.6.1 Testing Cumulative, Abandonment and Plateau Times Expert System (CAPTExS) Predictions of Cumulative Oil Production (Np) Applied to Multi-Phase Reservoirs with Bottom Water Drive (MPRBWD)

The above network returned an overall average error of 13.24%. Nevertheless it is meaningful to measure its performance with respect to each parameter. The network was successful in predicting the cumulative oil productions (Np) for 90 cases with an overall average error of about ~10.9%, where 59 cases with errors less than the overall average as displayed in **Figure 7.20.** Furthermore, 8 comparison plots of the CAPTExS_Np predicted cumulative productions and plateau and abandonment times versus their respective targets are shown in **Figure 7.21**. Whereas the overall average error for predicting the plateau times of the 90 cases was 31% and the abandonment times was 25.3%.

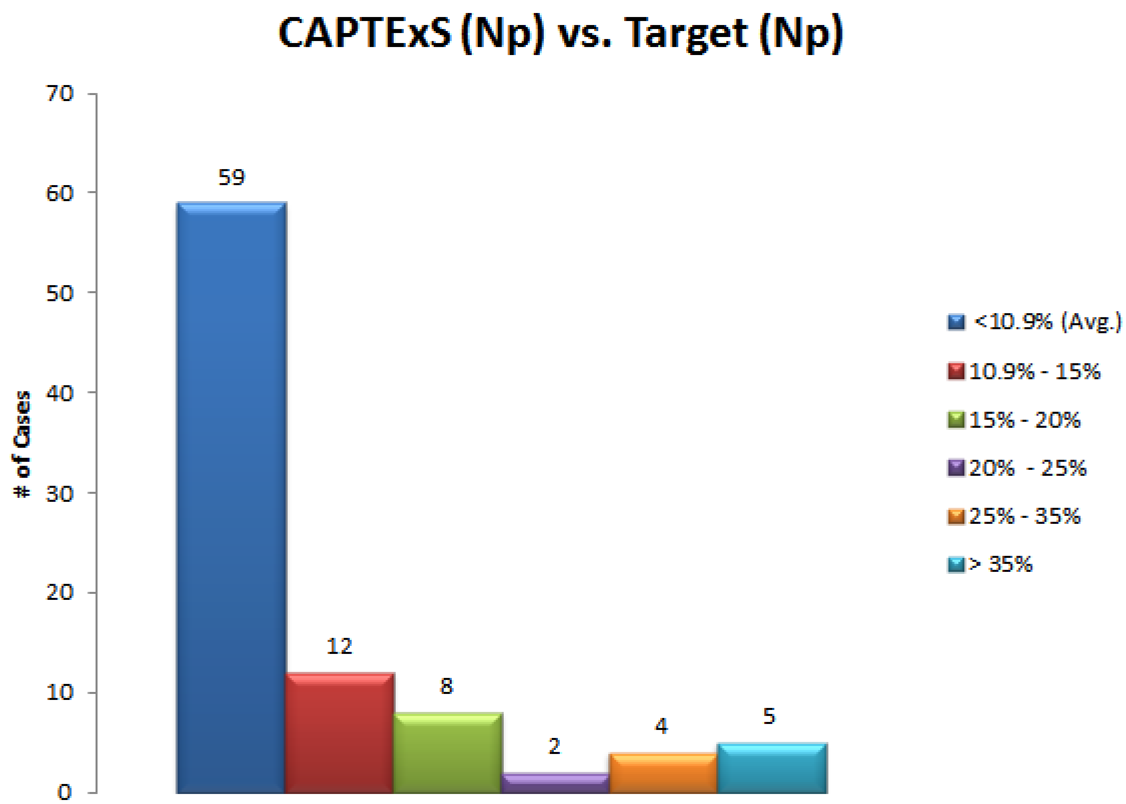


Fig. 7.20: CAPTExS Results and Their Respective Errors Implemented to MPRBWD.

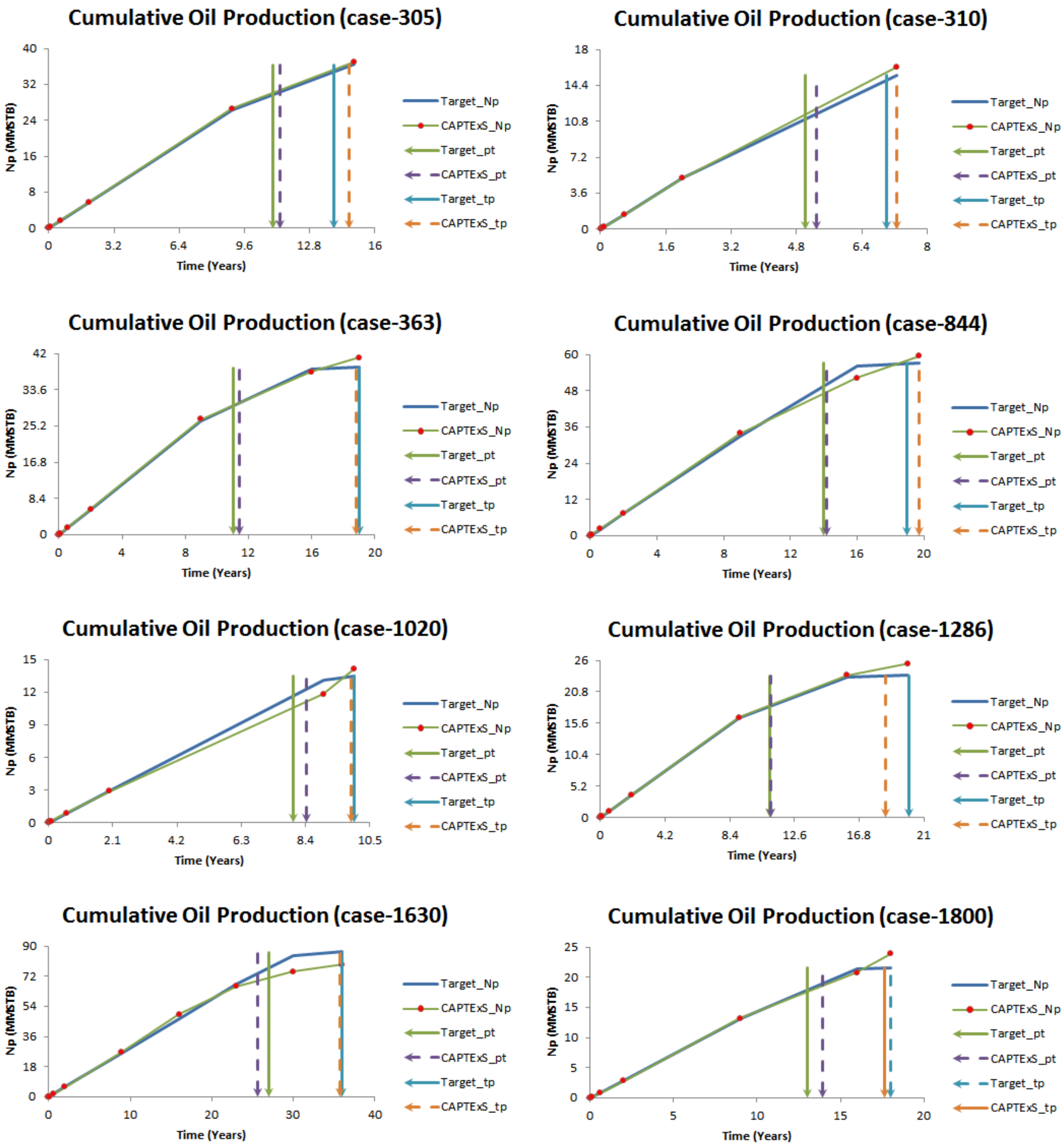


Fig. 7.21: Comparison Plots of the CAPTExS_Np, Plateau and Abandonment Times versus their respective Targets Implemented to MPRBWD.

7.6.2 Testing Cumulative, Abandonment and Plateau Times Expert System (CAPTExS) Predictions of Cumulative Gas Production (Gp) Applied to Multi-Phase Reservoirs with Bottom Water Drive (MPRBWD)

Simultaneously the network was successful in predicting the cumulative gas productions for the same 90 cases with an overall average error of about ~14%, where 68 cases with errors less than the overall average as displayed in **Figure 7.22.** Also the comparison plots of the same 8 cases are shown in **Figure 7.23**.

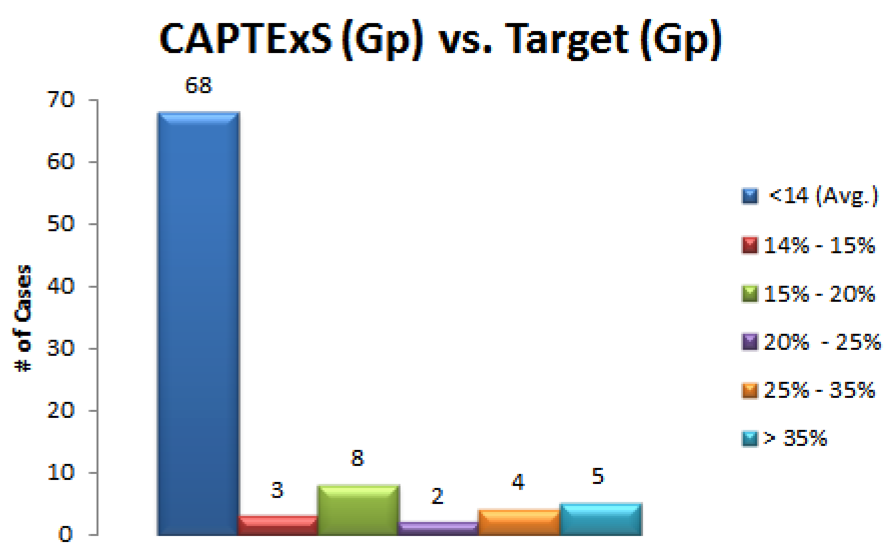


Fig. 7.22: CAPTExS Results and Their Respective Errors Implemented to MPRBWD.

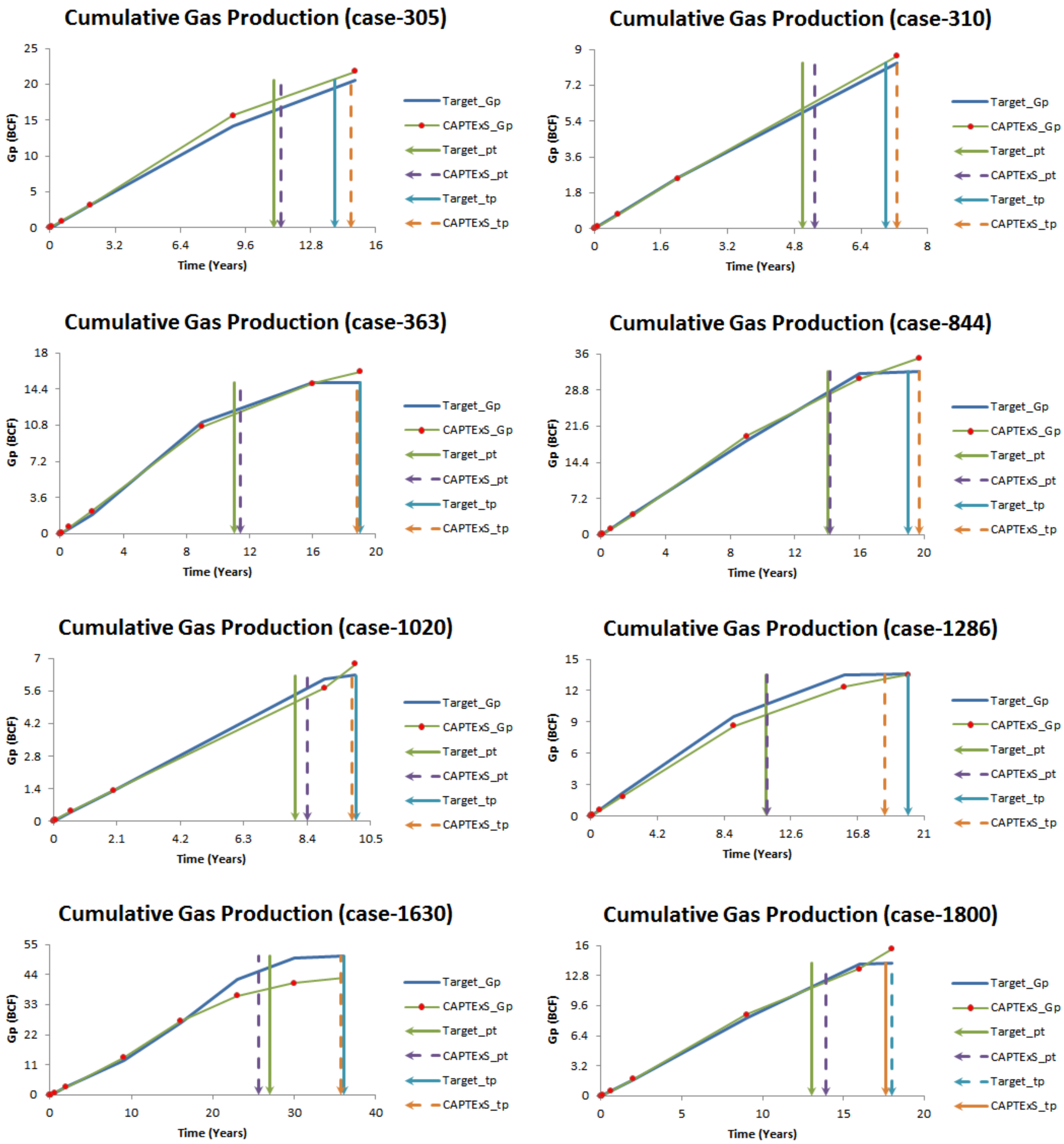


Fig. 7.23: Comparison Plots of the CAPTExS_Gp vs. Target_Gp Implemented to MPRBWD.

Chapter 8 Graphical User Interface and Summary

8.1 Integrated Artificial Expert Systems Graphical User Interfaces (GUIs)

The developed expert systems were compiled and assembled into a tool box that is user friendly, easy to install and does not require advance knowledge of the artificial neural networks running in the backgrounds. Without this assembly the benefits of the developed networks would be limited to those in close communication with the developer for a one on one showcase or those with background knowledge of how to set up the inputs for the ANNs and how to extract the results and present them in an informative manner. Therefore, the artificial expert systems graphical user interfaces are of great importance to the usefulness of the developed networks, their applicability and popularity. This section will highlight some of the integration and interactions between the expert systems. The GUIs were created using GUIDE, the MATLAB® graphical user interface development environment **(MATLAB®, 2011)**.

8.1.1 Main Window

The main window is the portal from which the user starts and selects the function he/she wants to perform. It first, lists which reservoir type the user would want to address, either the volumetric single phase gas reservoirs or the multi-phase reservoirs with bottom water drive as illustrated in **Figure 8.1**. Clicking on one of the pushbuttons will navigate the engineer to the desired model. **Figure 8.2** is displayed once the volumetric single phase gas reservoirs option is chosen.

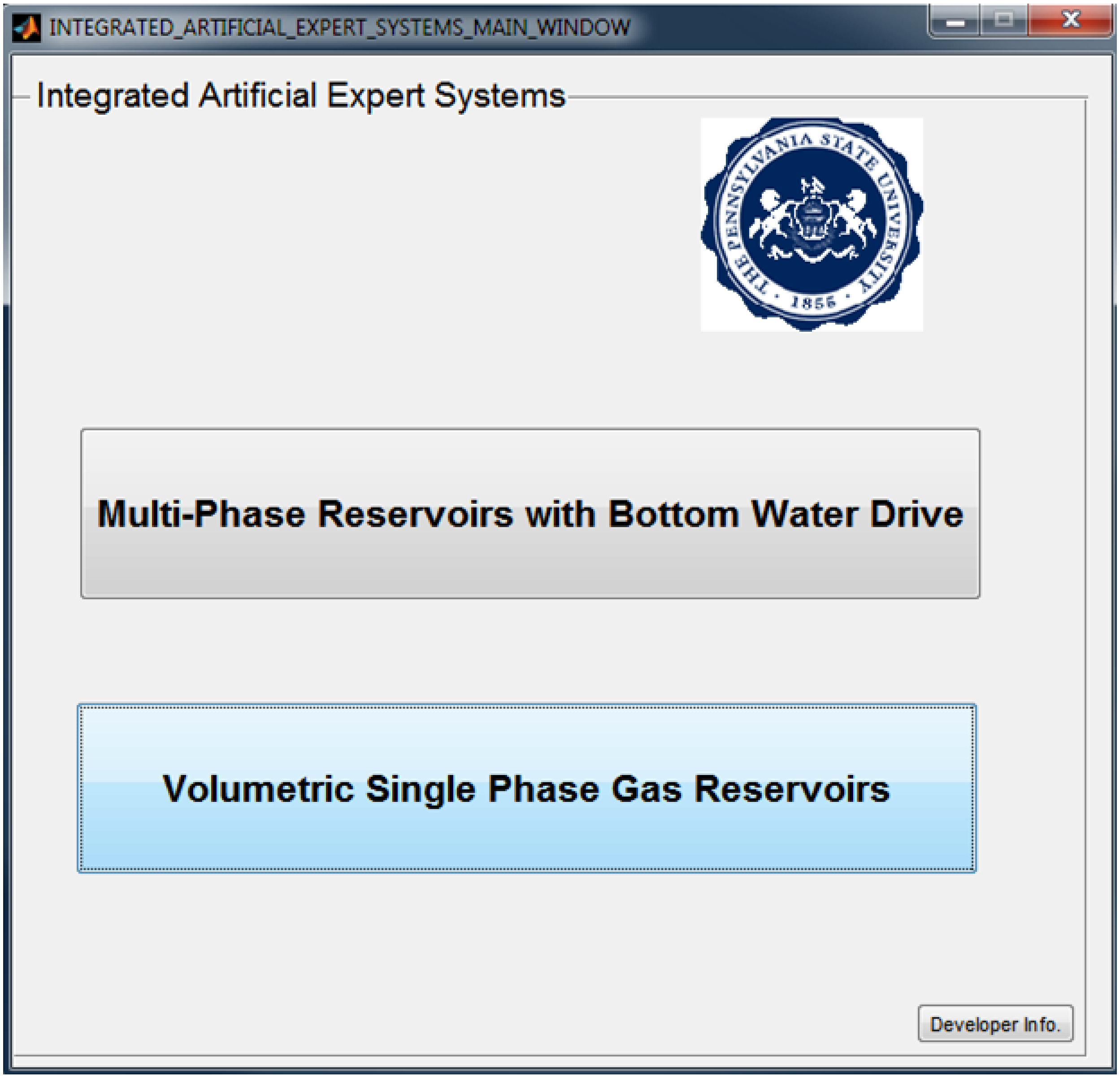


Fig. 8.1: Main Window of the Integrated Artificial Expert System Graphical User Interface (GUI).

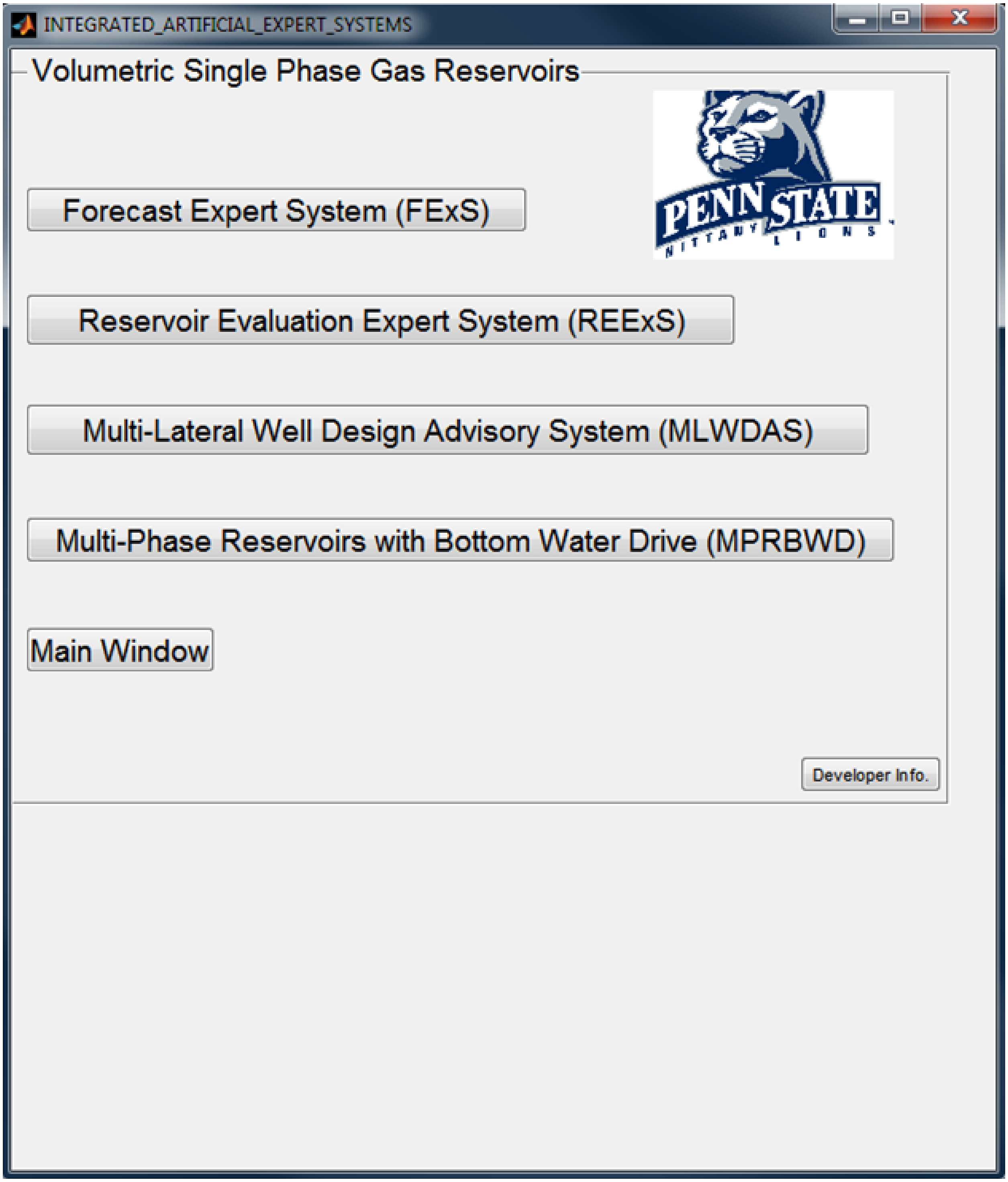


Fig. 8.2: Main Window of the Volumetric Single Phase Gas Reservoirs Expert System.

8.1.2 Reservoir Evaluation Expert System (REExS) GUI in the Volumetric Single Phase Gas Reservoirs (VSPGR) Model

In this environment the user would want to acquire some reservoir properties. The input parameters panel lists the editable boxes for entering the production time in units of months, the observed rates in MMscf/d, and the multi-lateral well design parameters. For simple illustration default values, that can be modified and saved by the user, are predefined and the observed rates are plotted and a 3D view of the well as illustrated in **Figure 8.3**. When the 'Evaluate' button in the output parameters panel is pressed it calls the REExS, which collects the user's entries from the input parameters panel and produces the required results. Furthermore, the user has the option to crosscheck these properties by reproducing the rate decline profile using the predicted properties and compare the new profile to the observed rate decline and returns the error in the designated box to the far right. The first column to the left under the cross checking panel will be populated with the rate values generated by the numerical simulator when the 'Forecast' button is clicked, which is the preferred tool to crosscheck with if it is accessible otherwise the RDExS can be used to regenerate the rates by pressing on the 'Forecast' icon above the right column. In addition, if the user is curious about the long term performance, by pressing on the button in the middle where it says 'Plot All' it will display a 50-year forecast by using both the numerical simulator, if it's accessible, and the FExS. The first three pushbuttons located at the bottom of the window are navigation buttons which can take the user back to either the main window, to the FExS GUI, or to the MLWDAS GUI respectively and the fourth one is just a clear button if the user chooses to clear his/her previous inputs and start with a new page. **Figure 8.4** demonstrates the REExS GUI with some examples of the mentioned features.

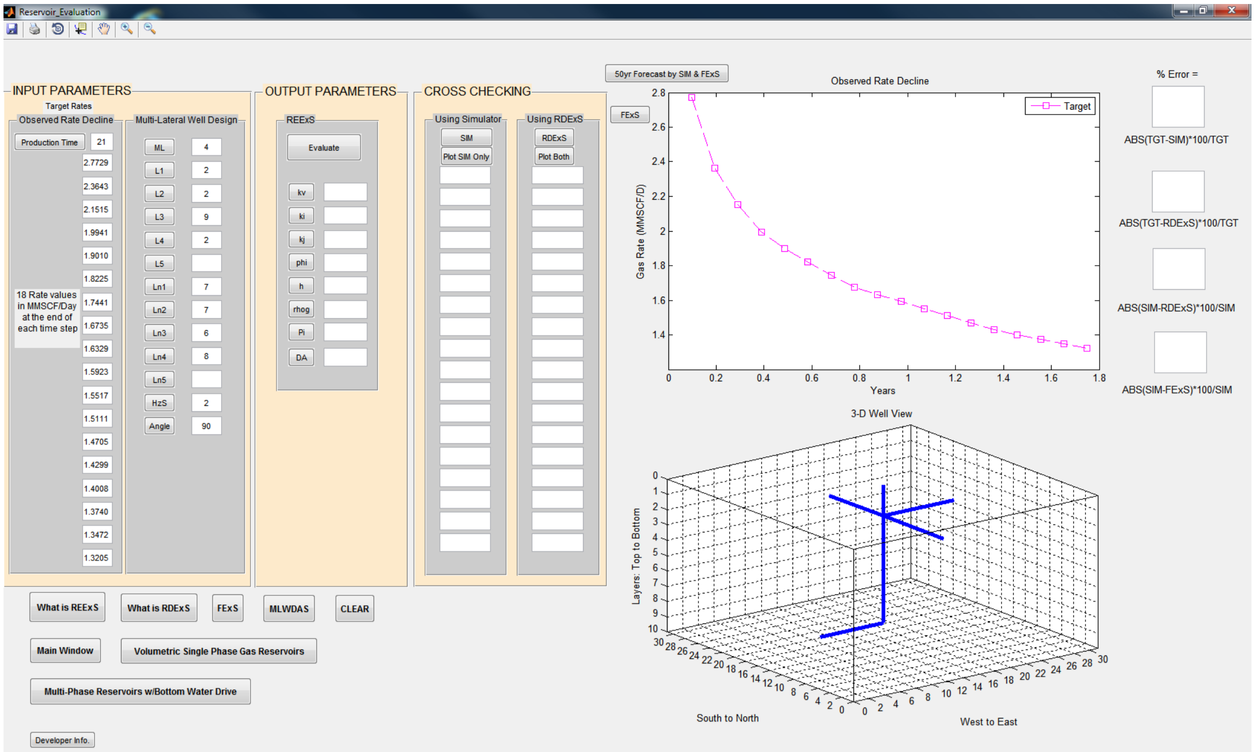


Fig. 8.3: Reservoir Evaluation Expert System (REExS) GUI under VSPGR Environment.

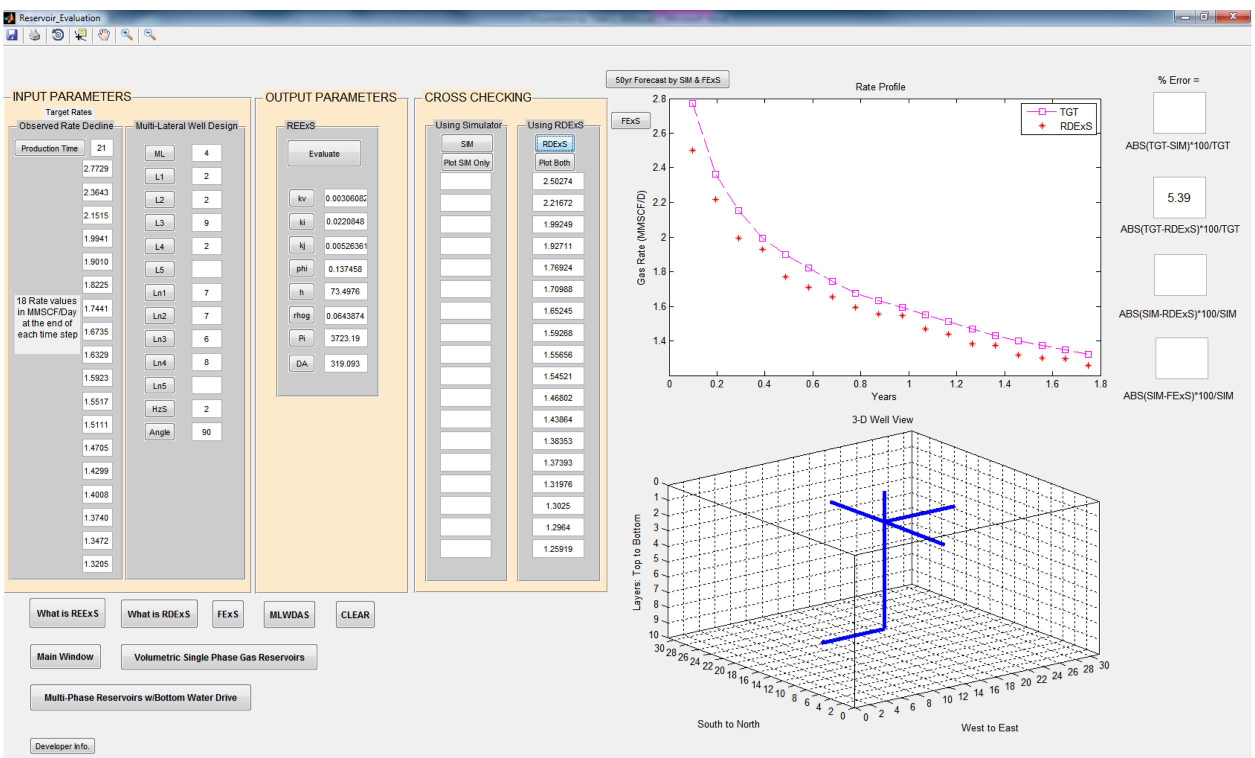


Fig. 8.4: REExS GUI Illustrating Some of its Produced Results.

8.1.3 Forecast Expert System (FExS) GUI

The purpose of this GUI is to provide the user with a long term forecast of the subject reservoir sector by entering basic knowledge of the multi-lateral well design and reservoir properties under the input parameters panel to the far left of the window as presented in **Figure 8.5**. Two forecasting options are available under the output parameters panel. One is forecasting using the numerical simulator, which should be the primary pick if it is available and the GUI can interface with it, the other one is forecasting using the developed FExS. Also the press button 'Using Both' will provide the performance results using both tools and the box to the far right will display the average error percentage.

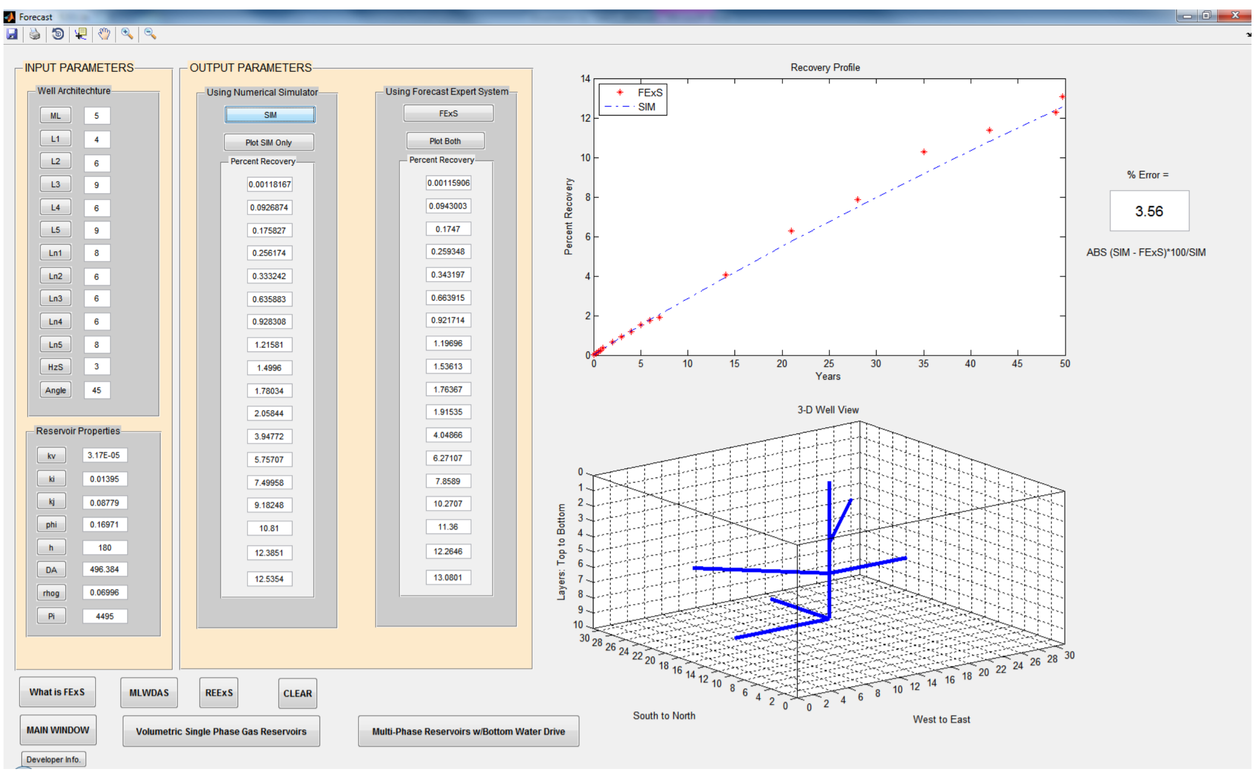


Fig. 8.5: Forecast Expert System (FExS) GUI under VSPGR Environment.

8.1.4 Multi-Lateral Well Design Advisory System (MLWDAS) GUI

Here the user is interested in knowing the design parameters of a well that will perform according to a predefined target and known reservoir properties. In this GUI that's exactly what the user needs to provide. The two columns to the far left shown in **Figure 8.6** are designated for entering the target recovery profile and the reservoir properties respectively. When the 'Design The Well' pushbutton is pressed the design parameters are generated and the 3D schematic of the well appears as in **Figure 8.7**.

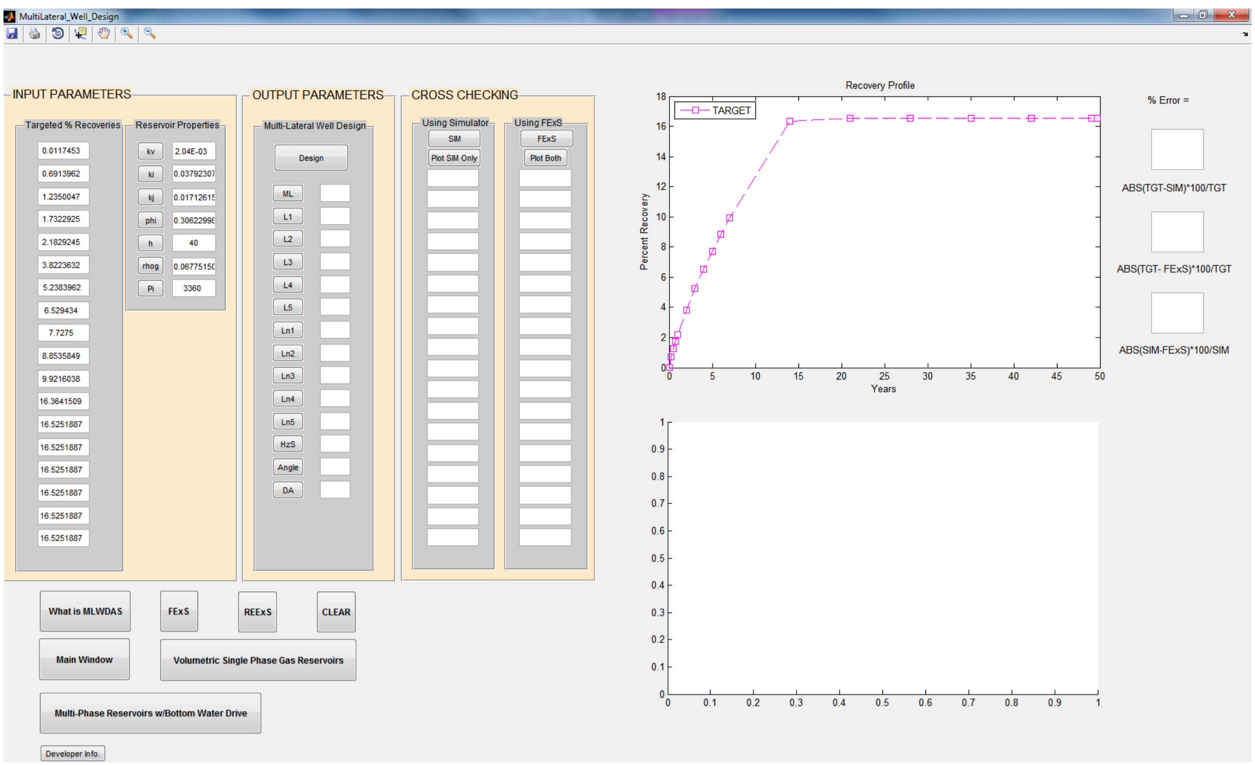


Fig. 8.6: Multi-Lateral Well Design Advisory System (MLWDAS) GUI under VSPGR Environment.

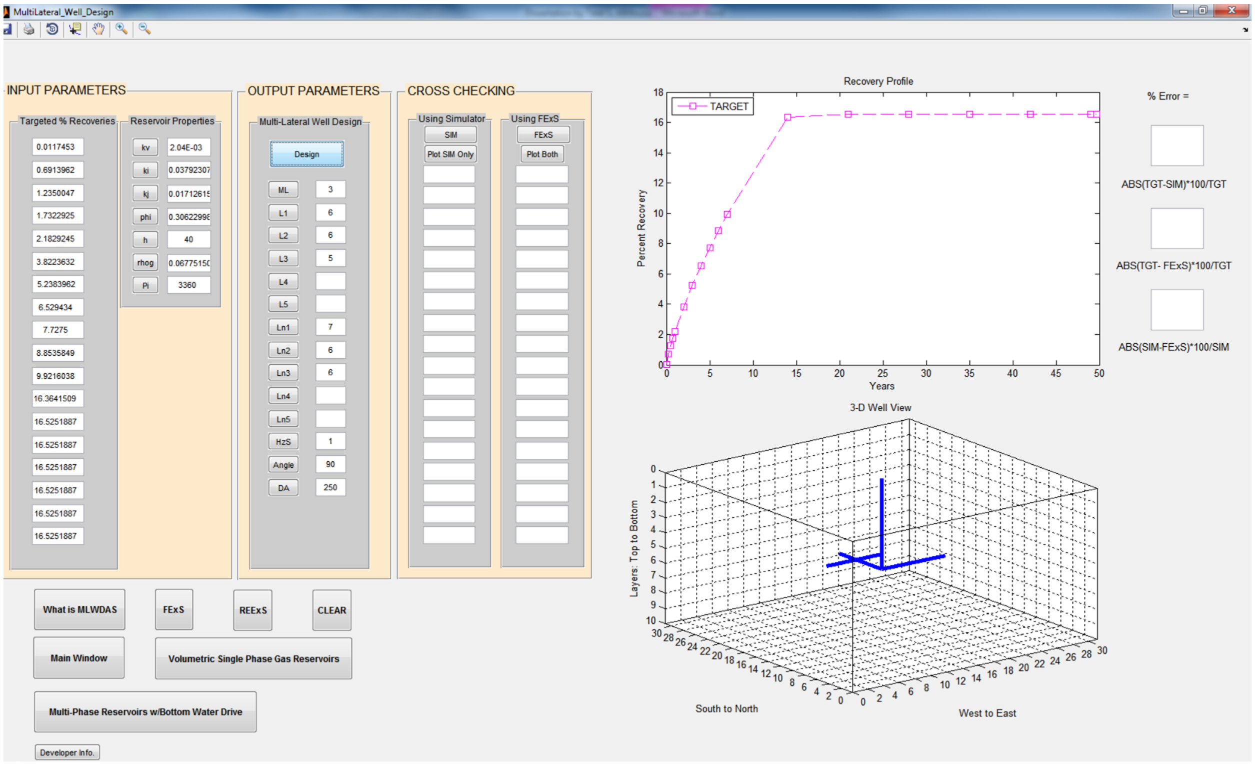


Fig. 8.7: MLWDAS GUI Showing the Well Design Parameters and the 3D View.

Furthermore, the crosschecking mechanism is also available by using the numerical simulator, priority if available, and the FExS. When either 'SIM' or 'FExS' or 'Plot All' pushbuttons is selected, the reservoir properties and the recommended multi-lateral well design parameters will be collected and entered into both engines to generate its respective recovery profiles forecast. Then the predicted profile will be compared to the target or desired profile and the error will be measured and displayed to the far right. If 'Plot All' is selected the error box on top shows the error between the target and the numerical simulator prediction; the second box in the middle is the error between the target and the FExS outputs, and the third one shows the error between the FExS and the numerical simulator as another crosscheck of the FExS. These features are illustrated in **Figure 8.8**.

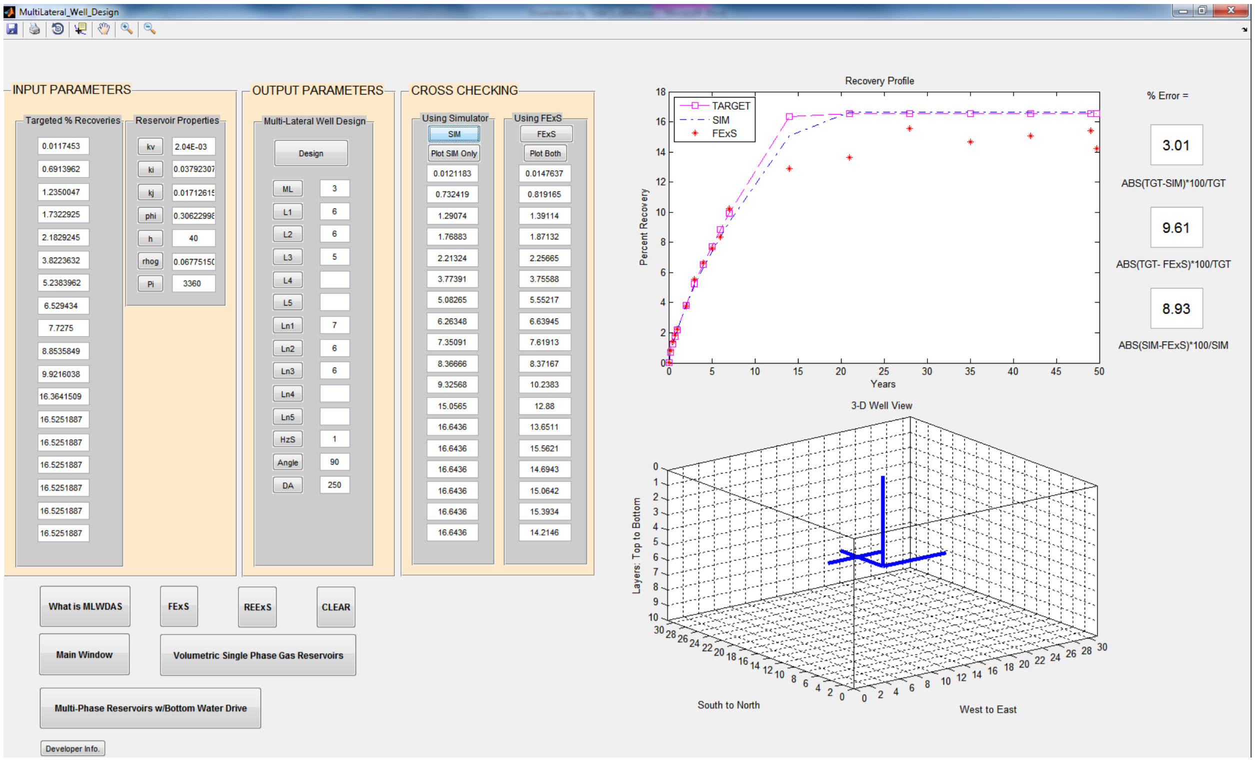


Fig. 8.8: MLWDAS GUI Showing the SIM and the FExS Predictions vs. the Target Cumulative Percent Recoveries and Corresponding Errors.

8.2 Summary

In this dissertation, an approach for developing and employing artificial expert systems in different petroleum engineering related aspects has been orchestrated. Illustrated the gradual progression in developing the integrated artificial expert systems for a wide spectrum of Volumetric Single Phase Gas Reservoirs (VSPGR) and Multi-Phase Reservoirs with Bottom Water Drive. The forward-looking networks serve as proxies to the numerical simulators when applicable, hence working as a buffer or a filtration mechanism since the engineer can analyze and go through many cases in a fraction of the time, labor, and expertise required by the conventional numerical simulators. This is expected to effectively enhance the efficiency at the workplace by saving time, efforts and money. Provided the inverse-looking solutions for predicting parameters for designing multi-lateral wells for a given set of targeted reservoir performances, and a second network that estimates critical reservoir properties from observed productions. The inverse-looking solutions are targeted to reduce the uncertainties and guide a design of a multi-lateral well and provide assistance in history matching problems by minimizing arbitrarily trial and error approaches and abuse usage of multipliers and modifiers.

The networks are developed in a fashion where they are intertwined and can be used for crosschecking each other in the absence of a higher fidelity tool. They have been assembled in a tool box with a user friendly interface to simplify its application without requiring knowledge of the background mechanism.

However it is emphasized that this dissertation is not suggesting the replacement of existing and well established procedures, protocols and know-how with the developed expert systems, but rather applying them as auxiliary, pre-screening or complimentary systems when and where applicable to ease of the computational overload, deliver a solution to the inverse-looking problems and enhance the overall decision-making process.

8.3 Recommendations

The author, motivated by his committee, recommends expanding on this work by future researchers, however not limited to these suggestions:

1- Expand to a full-field scale model where more wells are included in a single reservoir to understand and account for interference between wells.

2- Add economic parameters to multi-lateral well designs that can assist in screening and optimizing fit for purpose well architecture.

3- Address other reservoir types with different drive mechanisms.

4- Allow flexibility of the expert systems to account for different PVT and relative permeability tables for different reservoirs with ranging initial and connate saturations.

5- Designing graphical user interface for the developed expert systems is a powerful way to attract attention and spark a paradigm shift towards this line of research, hence increasing the size of enthusiasts will increase the number and improve the quality of future related studies.

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Appendix A

Sample Data Files

A.1 Sample Data File for Volumetric Single Phase Gas Reservoirs

```
RESULTS SIMULATOR IMEX 200900

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 31 31 10
KDIR DOWN
DI IVAR
 31*1.202654e+002
DJ JVAR
 31*1.202654e+002
DK ALL
 9610*7.349760e+000
DTOP
 961*3000
**$ Property: NULL Blocks  Max: 1  Min: 1
**$  0 = null block, 1 = active block
NULL CON            1
**$ Property: Porosity  Max: 0.2  Min: 0.2
POR CON          1.374580e-001
**$ Property: Permeability I (md)   Max: 0.1  Min: 0.1
PERMI CON          2.208480e-002
```

```
**$ Property: Permeability J (md)   Max: 0.1  Min: 0.1
PERMJ CON           5.263610e-003
**$ Property: Permeability K (md)   Max: 0.005  Min: 0.005
PERMK CON         3.060820e-003
**$ Property: Pinchout Array  Max: 1  Min: 1
**$  0 = pinched block, 1 = active block
PINCHOUTARRAY CON            1
CPOR 0.000001
MODEL GASWATER
TRES 150
PVTG EG 1

**$         p        Eg       visg
       14.696   4.81354  0.0113254
       247.05   84.1831  0.0116391
      479.403    170.17  0.0121176
      711.757   263.362  0.0127436
       944.11   363.994  0.0135319
      1176.46   471.576  0.0145019
      1408.82   584.477  0.0156674
      1641.17   699.795  0.0170259
      1873.52   813.864  0.0185532
      2105.88   923.227  0.0202077
      2338.23   1025.44  0.0219411
      2570.59   1119.27  0.0237088
      2802.94   1204.45  0.0254751
      3035.29   1281.34  0.0272138
      3267.65   1350.61  0.0289078
         3500   1413.08  0.0305474
DENSITY GAS 6.438740e-002
REFPW 14.696
DENSITY WATER 61.6381
BWI 1.01944
CW 3.1589e-006
VWI 0.47184
CVW 0.0
ROCKFLUID
RPT 1
SWT
```

```
**$        Sw       krw
         .22         0
          .3       .07
          .4       .15
          .5       .24
          .6       .33
          .8       .65
          .9       .83
           1         1
SLT
**$        Sl       krg
         .22         1
          .3     .8125
          .4        .5
          .5       .42
          .6       .34
          .7       .24
          .8        .1
          .9      .022
         .96         0
           1         0
INITIAL
VERTICAL DEPTH_AVE WATER_GAS EQUIL NOTRANZONE

REFDEPTH 3100
REFPRES 3.723190e+003
DWGC 3500

DATUMDEPTH 3100 INITIAL
NUMERICAL
RUN
DATE 1901 1 1
DTWELL 0.1

**$
     WELL  'Well-1'
     PRODUCER 'Well-1'
OPERATE  MIN  BHP  500.  STOP
MONITOR  MIN  STG  500000.  SHUTIN
**$          rad  geofac  wfrac  skin
GEOMETRY  I  0.25  0.37  1.  0.
     PERF  GEO  'Well-1'
**$ UBA     ff  Status  Connection
    18 16 2   1.  OPEN    FLOW-TO    'SURFACE'
    19 16 2   1.  OPEN    FLOW-TO  1
    20 16 2   1.  OPEN    FLOW-TO  2
    21 16 2   1.  OPEN    FLOW-TO  3
    22 16 2   1.  OPEN    FLOW-TO  4
    23 16 2   1.  OPEN    FLOW-TO  5

DATE 1931 1  1.00000
STOP
```

A.2 Sample Data File for Multi-Phase Reservoirs With Bottom Water Drive

```
RESULTS SIMULATOR IMEX 200900

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 31 31 10
KDIR DOWN
DI IVAR
 31*151
DJ JVAR
 31*151
DK ALL
 9610*6
DTOP
 961*5031
**$ Property: NULL Blocks  Max: 1  Min: 1
**$  0 = null block, 1 = active block
NULL CON           1
**$ Property: Porosity  Max: 0.2  Min: 0.2
POR CON          1.500000e-001
**$ Property: Permeability I (md)   Max: 0.1  Min: 0.1
PERMI CON          236
**$ Property: Permeability J (md)   Max: 0.1  Min: 0.1
PERMJ CON          164
**$ Property: Permeability K (md)   Max: 0.005  Min: 0.005
PERMK CON        1.640000e+001
AQUIFER BOTTOM
```

```
AQMETHOD FETKOVITCH
AQPROP

**$thickness   porosity     permeability radius       angle
       0.0           0.0           1.640000e+001      0           0
CPOR 4.13685E-006
PRPOR 200
MODEL BLACKOIL
TRES 150
PVT 1

**$         p        rs           bo        Eg          viso         visg
           101.53      38.19        1.12      32.41        1.11
      0.01262
           232.06      97.11        1.17      69.70        0.96
      0.01349
           329.24      122.72       1.18      95.93        0.95
      0.01371
           458.32      151.14       1.18      134.69       0.88
      0.01401
           672.98      190.91       1.21      198.43       0.83
      0.01434
           932.59      233.99       1.22      274.31       0.79
      0.01485
           1232.82     292.96       1.25      367.83       0.74
      0.01535
           1811.52     398.16       1.30      539.47       0.70
      0.01657
           2506.25     523.41       1.34      745.77       0.59
      0.01849
           3039.99     605.35       1.39      896.07       0.54
      0.02040
           4999.45     1132.75   1.49      1447.73     0.30 0.02741
           6999.52     2020.00   1.60      2010.63     0.23 0.03456
       10000.35    3350.91   1.76      3446.68     0.20     0.05281
CO 7.8324E-006
CVO 2.0767E-004
DENSITY OIL 5.770000e+001
DENSITY GAS 5.800000e-002
REFPW 14.769
DENSITY WATER 71.979
BWI 1.01
CW 2.999e-006
VWI 1.29
CVW 0.0
ROCKFLUID
RPT 1
SWT
**$  SW      KRW         KROW          PCOW
       0.200   0.0000      1.0000      28.404
       0.229    0.0001      0.7407      13.807
       0.255    0.0003      0.6829      8.702
```

```
       0.308    0.0012      0.5722      3.190
       0.334    0.0023      0.5194      2.726
       0.412    0.0102      0.3715      1.827
       0.464    0.0219      0.1526      1.222
       0.557    0.0416      0.0822      0.638
       0.606    0.0721      0.0000      0.191
       0.647    0.1448      0.0000      0.000
       0.700   0.1780      0.0000      0.000
       0.800   0.2604      0.0000      0.000
       1.000   1.0000      0.0000      0.000
SLT
**$   SL      KRG         KROG          PCOG
       0.200   1.0000      0.0000      564.429
       0.316    0.6784      0.0000      84.064
       0.435    0.6215      0.0000      54.012
       0.562    0.5456      0.0000      35.172
       0.614    0.3939      0.0020      8.818
       0.702    0.1399      0.0280      5.397
       0.812    0.0515      0.1721      1.980
       0.875    0.0297      0.3395      1.516
       0.906    0.0226      0.4395      1.305
       0.937    0.0173      0.5500      1.089
       0.969    0.0131      0.6702      0.856
       1.000    0.0000      1.0000      0.000
INITIAL
VERTICAL BLOCK_CENTER WATER_OIL_GAS

PB CON 2189
REFDEPTH 5061
REFPRES 2189
DGOC 5025
DWOC 5121

NUMERICAL
RUN
DATE 2013 1 1
DTWELL .04167

**$
      WELL  'Well-1'
      PRODUCER 'Well-1'
OPERATE  MAX  STO  6000 CONT
OPERATE  MIN  BHP  14.7  *CONT
MONITOR  MIN  STO  50.0   SHUTIN
MONITOR  MAX  GOR  4000.0 SHUTIN
MONITOR  MAX  WCUT 0.99   SHUTIN
**$          rad  geofac  wfrac  skin
GEOMETRY  I  0.25  0.37  1.  0.
      PERF  GEO  'Well-1'
**$ UBA     ff  Status  Connection
    15 16 6   1.  OPEN    FLOW-TO    'SURFACE'
    14 17 6   1.  OPEN    FLOW-TO  1
```

```
    13 18 6   1.  OPEN    FLOW-TO  2
    12 19 6   1.  OPEN    FLOW-TO  3
    11 20 6   1.  OPEN    FLOW-TO  4
    10 21 6   1.  OPEN    FLOW-TO  5
    9 22 6   1.  OPEN    FLOW-TO  6
    17 16 2   1.  OPEN    FLOW-TO  1
    18 16 2   1.  OPEN    FLOW-TO  8
    19 16 2   1.  OPEN    FLOW-TO  9
    20 16 2   1.  OPEN    FLOW-TO  10
    16 15 8   1.  OPEN    FLOW-TO  1
    16 14 8   1.  OPEN    FLOW-TO  12
    16 13 8   1.  OPEN    FLOW-TO  13
    16 12 8   1.  OPEN    FLOW-TO  14
    16 11 8   1.  OPEN    FLOW-TO  15
    16 10 8   1.  OPEN    FLOW-TO  16

DATE 2014 1  1.00000
DATE 2016 1  1.00000
DATE 2018 1  1.00000
DATE 2020 1  1.00000
DATE 2022 1  1.00000
DATE 2024 1  1.00000
DATE 2026 1  1.00000
DATE 2028 1  1.00000
DATE 2030 1  1.00000
DATE 2032 1  1.00000
DATE 2034 1  1.00000
DATE 2036 1  1.00000
DATE 2038 1  1.00000
DATE 2040 1  1.00000
DATE 2042 1  1.00000
DATE 2044 1  1.00000
DATE 2046 1  1.00000
DATE 2048 1  1.00000
DATE 2050 1  1.00000
DATE 2052 1  1.00000
DATE 2054 1  1.00000
DATE 2056 1  1.00000
DATE 2058 1  1.00000
DATE 2060 1  1.00000
DATE 2062 1  1.00000
DATE 2072 1  1.00000
DATE 2083 1  1.00000
STOP
```

Vitae

Talal Saeed AlMousa

Talal was born in Riyadh, Saudi Arabia in October of 1976, the eldest of 8 brothers and six sisters. He joined Saudi Aramco in August of 1995 immediately after high school. A year later, the company awarded him a scholarship to the United States where he attended Louisiana State University (LSU), Baton Rouge, Louisiana, for five semesters (08/96 – 12/98). He then transferred to King Fahd University of Petroleum and Minerals (KFUPM), Dhahran, Saudi Arabia, where he earned his Bachelor's of Science degree in petroleum engineering in 2002.

In July 2002 Talal joined Saudi Aramco's workforce as a reservoir management engineer and became a member in the Society of Petroleum Engineers (SPE). As part of his development plan, in July 2003 Talal was assigned to work as a log analyst with reservoir description group. In January 2004 he assumed drilling engineer responsibilities with deep gas drilling division. Then he worked as a production engineer for one year from 07/04 – 06/05. In July 2005 Talal returned to reservoir management department where he had the opportunity to manage mature fields, participate in the development of a new increment and author and co-author two SPE papers in the area of production engineering and rock mechanics.

Talal enrolled at KFUPM as a part-time graduate student in August 2005 while holding a fulltime job as a reservoir engineer with Saudi Aramco. He earned his Master's of Science degree in petroleum engineering in June 2008. Talal was elected to join the Technologist Development Program (TDP), an in house program designed by Saudi Aramco, to achieve specialist status in reservoir management of intelligent fields. In August 2009 Talal was granted a second scholarship by Saudi Aramco to attend the Ph.D. program at The Pennsylvania State University (PSU). He successfully defended his dissertation on June 24, 2013 and earned his Doctoral degree in energy and mineral engineering with option in petroleum and natural gas engineering in August 2013. Soon after his graduation he resumed his role with Saudi Aramco in Dhahran, Saudi Arabia as a reservoir management engineer. He can be reached any time at mousats@gmail.com.