Applications of Artificial Expert Systems in the Diagnosis and Analysis of Unexpected Spatial and Temporal Changes in Reservoir Production Behavior

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by

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Abstract

In reservoir simulation, the history matching process can easily become a time sink. Since conventional history matching involves manual input, most guidelines suggest a simplified model be used, and only the parameters that influence the outcome and those with the highest uncertainty be changed (Carlson, 2003). However, even with this simplification, the process of history matching still consumes a considerable amount of time. Moreover, as the complexity of the reservoir increases, the time required to perform a successful history match increases as well. After achieving a satisfactory history match, one is set to perform forecasting studies. Forecasting is the ultimate objective of a simulation study. In later times, if the prediction is not in agreement with the observed data, history matching parameters need to be re-tuned. After this tune-up process, predictions should be close enough to the observed data. When observed data deviates from predictions, reservoir engineers then have the daunting task of identifying the causes of such deviation in a rather short period of time to ensure that necessary preventive measures can be implemented promptly.

Expert systems can be used to assist reservoir engineers with refining and re-evaluating their history matching parameters. In this proposed study, an artificial expert system is developed, which in turn provides the reservoir engineer with a good set of starting points to pick the history matching parameters for a newly created reservoir simulation model. The same expert system can also help in fine-tuning the parameters if the model is already history matched. For complex models, the expert system can use new production data to improve the history matching parameters.
Once the prediction process is under way, the expert system can be expanded into a suit of diagnostic tools to detect changes in reservoir responses that might occur over time. These problematic changes in responses can be caused by the alteration of the area around the well or from other geomechanical changes that take place within the reservoir. These developed tools are triggered when the well production profile behaves unexpectedly. The first tool looks into the possibility of a developed skin around the well may have caused the decline in production. Another tool evaluates whether a set of perforations have been plugged. If the reservoir has hydraulically fractured wells, an expert tool is used to analyze the fracture effective permeability and length to see if they match the specifications of the fracture job. Two more tools are used to assess two geomechanical features of the reservoir. The first one can help figure out if the production changes are caused by the reservoir compaction and the second looks into the possibility of tarmat breakage at the base of the hydrocarbon column. The last tool looks to identify areas of the reservoir where there is a possibility of having natural fractures. Coupled with the engineer’s expertise, the expert system can be extended to more complex scenarios. It is worth noting that each expert system is explicitly developed for a specific reservoir and is not interchangeable with other reservoirs.

The last part of this research involves developing graphical user interfaces (GUIs) that provide user-friendly interfaces for the engineers to input and edit the data and generate numerical and graphical results. It will also enable the engineers to validate the results with the numerical reservoir simulator.

In this research, the assisted history matching expert system has shown its ability to bring the reservoir properties used by the reservoir simulation model closer to their
original values. In addition, it has helped in reducing the uncertainty ranges for the different parameters used in the history matching process. The diagnostic expert systems have also shown the strength of the artificial intelligence protocol applied in these systems. For the forward solution part, all diagnostic expert systems show excellent results and thus can be safely utilized as proxies to the reservoir simulator. The backward solution part is more difficult to achieve. However, except the tarmat breakdown expert system, all diagnostic expert systems have shown satisfactory accuracy as identified by the user. The tarmat breakdown expert system, performed very well when only one area of the tarmat layer is broken whereas it struggled when another area of the tarmat broke at a later time.
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Chapter 1 Introduction

Critical decision-making has long been part of the petroleum engineers’ responsibility. One of the most trusted tools an engineer can use to help in the decision-making process is the numerical reservoir simulator. Constructing a reservoir model is a complex process that involves data acquisition, geological evaluation, reservoir characterization, geostatistical calculations, upscaling, stochastic modeling, initialization, and history matching before it can be used for any reservoir related studies. The most challenging obstacle that can diminish the quality of the reservoir simulation model is the data availability and quality. Typically, data is mostly available around the wells, thus inter-well area characteristics must be geostatistically computed. Hence, history matching is performed after constructing the geological model. The process of history matching involves changing the reservoir properties, either manually or automatically, until an acceptable match of saturations, rates and pressures between the simulation model and the field’s observed data is achieved. Once the match is achieved, the model can then be used to forecast reservoir performance more confidently. History matching is a time-consuming and computationally intensive and expensive task. It requires highly skilled engineers and geoscientists and powerful computational hardware.

Artificial expert systems have been successfully applied in many petroleum engineering applications. Artificial neural networks, which are the main component of the expert systems used in this research, are computational elements that imitate the process of the biological neurons. These networks are powerful tools that can solve many non-linear problems by mapping the input data into a meaningful output. A neural network needs to be trained with provided data to learn the relationship between the input
and output and then can perform generalization on new sets of data. Neural networks can work effectively with reservoir simulation studies. If properly trained, they can serve as proxy models to the reservoir simulation and provide reservoir performance in a fast and efficient way. They can also be trained to predict different reservoir properties when provided with the reservoir performance data.

In this research, an expert system is developed that can help the reservoir simulation engineer determine the initial reservoir parameters to start the history matching process for a newly developed reservoir model. The expert system can also be applied to an already history matched model where the expert system can fine-tune the reservoir parameters and bring them closer to their actual values. For more complex reservoirs that are difficult to match, the expert system can utilize new production data to reduce the uncertainty in the reservoir parameters. This is an iterative process that can improve the accuracy of the history match without eliminating the expert input of the reservoir engineers. The required data to train the neural network is generated using a commercial reservoir simulator package.

The expert system can be extended beyond assisted history matching. Artificial expert systems have been effectively applied to diagnose unexpected behavior of the reservoir. When the reservoir model is history matched, it is expected to produce quite accurate predictions. However, deviation from the expected trend can occur without immediate explanation. The reservoir engineer needs to list the possible factors that may cause such deviation, based on his/her knowledge of the reservoir. Expert tools are then built to accommodate each factor. Several examples of expert systems that can serve as a diagnostic tool are developed in this research.
Formation damage is always a challenge to healthy reservoir production. An expert system is built to evaluate whether the skin around the well has caused the unexpected decline in production. Another expert system evaluates perforation sets to see if they are partially or fully open. A third expert system is associated with hydraulically fractured wells. All fracture jobs specify the permeability and length of the fracture. This tool examines whether the actual hydraulic fracture are the same as planned.

Geomechanical properties of the reservoir can cause unexpected production behavior. An expert system is developed to assess the reservoir compaction effect on porosity and permeability and evaluate the impact on the production performance. Tarmat exists in many reservoirs, specifically in the Middle East. An expert system is developed to predict the location and time of the tarmat breakage when unexpected reservoir performance is encountered. Natural fractures exist in many reservoirs around the world. Another expert system is developed to identify areas of the reservoirs where there is a possibility of having natural fractures. All these variations can then be incorporated into the reservoir model to account for the changes in reservoir performance and keep the model up-to-date.

This suite of tools will hopefully help reservoir engineers in the decision-making process. However, it is important to emphasize that the expert systems are not meant to replace the conventional reservoir simulator. Rather, they can be used as complimentary tools to cut computational time and provide educated estimations of the critical reservoir properties that need attention while making decisions.
Chapter 2 Literature Review

2.1 Overview of Reservoir Simulation

“A simulation model is one which shows the main features of a real system, or resembles it in its behavior, but is simple enough to make calculations on. These calculations may be analytical or numerical” (Sorbie, 2004). A reservoir simulation model combines physics, mathematics, reservoir engineering, and computer programming to develop a tool that can predict reservoir performance subject to different operating conditions. The need to use reservoir simulation arises from the fact that petroleum and gas projects are immensely expensive with high degree of uncertainty. The risk in these projects must be assessed and eventually minimized (Ertekin et al., 2001).

Reservoir performance can be predicted using three models: analogical, experimental, and mathematical. Analogical models rely on mature fields that share similar geological or petrophysical properties to the target reservoir. This method is only practical when the available data is scarce. Experimental models measure the reservoir characteristics in laboratory and scale the results to the entire target reservoir. Mathematical models use equations to predict reservoir performance. These equations include material balance, decline curve, statistical methods, and analytical methods (Ertekin et al., 2001).

Typically, all reservoir simulation studies apply Darcy’s law in the calculation of fluid flow in the reservoir:

\[ Q = -\frac{k (P_b - P_a)}{\mu L} \]  

(2.1)
where, $Q$ is the unit volume per time, $k$ is the permeability, $\mu$ is the viscosity, $P_b - P_a$ is the pressure drop, and $L$ is the length. The following assumptions are implied in the law:

- The fluid is homogeneous, single-phase and Newtonian
- No chemical reaction takes place between the fluid and porous medium.
- Laminar flow conditions apply.
- Permeability is independent of pressure, temperature, and the flowing fluid. It is a property of the porous medium.
- There is no slippage effect.
- There is no electro-kinetic effect (Islam et al., 2010).

There are two broad approaches to analyze multi-phase fluid flow in porous media inside the reservoir. These are the black oil compositional and models. Black oil models assume the composition of oil and gas is fixed and the solubility of the gas in the oil depends on pressure only (Islam et al., 2010). The need for compositional simulators arises when an equation of state is required to describe the fluid phase behavior or compositional changes associated with space and time. Compositional simulators are typically used to study condensates or volatile crude oil, gas injection, and secondary recovery studies. In both approaches, mass balance equations are used. Temperature is assumed constant and hence the use of energy balance is not needed. However, processes such as steam injection and in-situ combustion have necessitated the use of thermal simulators. These simulators use the compositional approach, where energy equations and mass balance equations are applied simultaneously (Chidambaram, 2009).
A typical reservoir simulation study starts with data gathering. All initial data are screened for quality. Then geological maps of porosity, permeability, and net pay are constructed in a grid format. Initialization then takes place; initial water saturation is populated to all grid blocks based on the available capillary pressure data and the original oil in place is determined. The process of history matching is then performed. The numerical model is run through time with the observed rates and pressure specified in the model input. The idea is to match the reservoir performance in terms of rates, pressure, GOR, etc. Once a good history match is achieved, predictions take place. Different production scenarios can be examined to determine the best development strategy. The final stage is to present the output of the simulation study in a meaningful report that can guide decision makers towards a common sense development strategy (Carlson, 2003). Figure 2.1 represents a typical reservoir simulation process.

2.1.1 History Matching

The history matching main objective is to improve and validate the reservoir simulation model parameters. The process of history matching involves adjusting the model parameters aiming to obtain a model output that acceptably matches the production history. Once that is achieved, the confidence level of predictions becomes high. Figure 2.2 shows the steps performed during a history match. There are two approaches used for the history matching process: manual and automatic history matching. Typically, manual history matching is used more frequently. Manual history matching is performed by running the simulation model through time and after each run the history match output is compared to the actual field performance. The reservoir
simulation engineer then makes an educated adjustment to the field parameter based on his experience of the reservoir in order to improve the match.

![Typical reservoir simulation process](image)

**Figure 2.1:** Typical reservoir simulation process. Source: (Carlson, 2003)

Automatic history matching is similar to manual history matching except that it involves computer logic to adjust the reservoir parameters rather than direct engineering involvement. One downside of automatic history matching is that it might remove engineering judgment and knowledge from the history matching process. A common approach to automatic history matching is to minimize an error function (objective function) between the observed data and the reservoir simulation output data. The error function can be of the form:

$$ S = \sum_{i=1}^{n_{par}} [w_i (X_{io} - X_{is})^2] $$

(2.2)
where $S$ is the error function, $w$ is a weight factor, and $X_i$ is any parameter that is to be matched during history matching (Ertekin et al., 2001).

1. Set the objectives of the history-matching process.

2. Determine the method to use in the history match. This should be dictated by the objectives of the history match, company resources available for the history match, the deadlines for the history match, and data availability.

3. Determine the historical production data to be matched and the criteria to be used to describe successful match. These should be dictated by availability and quality of the production data and by the objectives of the simulation study.

4. Determine the reservoir data that can be adjusted during the history match and the confidence range for these data. The data chosen should be those that are the least accurately known in the field but that have the most significant impact on reservoir performance. This step should be performed in conjunction with the reservoir engineers, geologists, and field operating staff working on the field under study.

5. Run the simulation model with the best available input data. During the pressure-match stage of the history match the reservoir-voidage rates (oil rate plus free-gas rate plus water rate at reservoir conditions) are specified. During the saturation stage of the history match, oil rates (for an oil reservoir) or gas rates (for a gas reservoir) at standard conditions are specified.

6. Compare the results of the history match run with the historical production data chosen in Step 3.

7. Change the reservoir data selected in Step 4 within the range of confidence.

8. Continue with Step 5 through 7 until the criteria established in Step 3 are met.

Figure 2.2: Overall iterative procedure for history matching. Source: (Ertekin et al., 2001)
There exist some general guidelines for performing a history match. Among them are:

- Use the simplest model possible.
- Keep the changes to the parameters with the most influence on answer.
- Keep the changes to the parameters with the highest uncertainty (Carlson, 2003).

### 2.1.1.1 Data Input and Output

Prior to conducting any reservoir simulation study, the system to be modeled should be well understood. Table 2.1 lists the data requirement for a reservoir simulation study.

**Table 2.1: Data Requirements for a Simulation Study. Source: (Fanchi, 2006)**

<table>
<thead>
<tr>
<th>Property</th>
<th>Sources</th>
</tr>
</thead>
<tbody>
<tr>
<td>Permeability</td>
<td>Pressure transient testing, Core analyses, Correlations, Well performance</td>
</tr>
<tr>
<td>Porosity, Rock compressibility</td>
<td>Core analyses, Well logs</td>
</tr>
<tr>
<td>Relative permeability and capillary pressure</td>
<td>Laboratory core flow tests</td>
</tr>
<tr>
<td>Saturations</td>
<td>Well logs, Core analyses, Pressure cores, Single well tracer tests</td>
</tr>
<tr>
<td>Fluid property (PVT) data</td>
<td>Laboratory analyses of reservoir fluid samples</td>
</tr>
<tr>
<td>Faults, boundaries, fluid contacts</td>
<td>Seismic, Pressure transient testing</td>
</tr>
<tr>
<td>Aquifers</td>
<td>Seismic, Material balance calculations, Regional exploration studies</td>
</tr>
<tr>
<td>Fracture spacing, orientation, connectivity</td>
<td>Core analyses, Well logs, Seismic, Pressure transient tests, Interference testing, Wellbore performance</td>
</tr>
<tr>
<td>Rate and pressure data, completion, and workover data</td>
<td>Field performance history</td>
</tr>
</tbody>
</table>

History matching process is usually performed over two stages: pressure match and saturation match. During the pressure match stage, the reservoir energy should be strongly considered. The most appropriate production data to choose during this stage of the matching process is the historical well voidage rate; that is the sum of the oil, free
gas, and water rates at reservoir conditions. The viodage rate will ensure accurate material balance calculations. However, individual rates might not be correctly identified. During the saturation match stage, the production rate to be specified are the oil rate for oil reservoirs and the gas rate for gas reservoirs. This will simplify the process of matching the historical data (Ertekin et al., 2001).

2.1.1.2 History Match Quality

The definition of a successful history match is different from one organization to the other since there is no industry standard that describes what a successful history match is. The type of the performed study should dictate the terms for a successful history match. If a coarse study is being performed, then a difference of ±10% between calculated and observed pressure is usually acceptable. If the study is more demanding, then the tolerance may be reduced to ±5% or even less. However, it is unrealistic to seek a tolerance of less than ±1%. Another indicator of the quality of the history match is the match of WOR, GOR, or water cut. Adjusting the model parameters to improve the quality of each factor is a key to achieving a good history match. It should be also noted that matching every well is virtually impossible, so again the reservoir simulation engineer has to identify the accuracy of the model that best suits the purpose of his/her study (Fanchi, 2006).

2.1.2 Predictions

Predicting reservoir performance is the next stage after a good history match is achieved. In this stage of study, the reservoir simulation model is used to predict future reservoir performance (Ertekin et al., 2001). To start with the prediction process, a base
case prediction model needs to be prepared. The base case model is a forecast that assumes existing operating conditions still apply. It establishes a basis from which to compare changes in field performance resulting from changes in existing operating conditions (Fanchi, 2006).

2.1.2.1 Prediction Capabilities

Performance prediction carries valuable information that can help reservoir engineers better understand their reservoir. Prediction can be used to interpret and understand reservoir behavior when any of the operating conditions changes. This can be done through a sensitivity analysis study where the reservoir parameters are assessed and risk analysis is obtained. Predictions also enable engineers to estimate project life by predicting the recovery profile. Economic constraints can be fed into the reservoir model in order to create different scenarios for reservoir development. Another important capability of a prediction model is the preparation of a reservoir management plan (Fanchi, 2006). Each reservoir engineer has to present an anticipated monthly or quarterly operating plan. The most reliable source is the reservoir prediction model.

2.1.3 Other Relevant Work

Dye et al., (1986) presented a new approach to automated history matching. The authors introduced a “reservoir engineering-oriented” approach, which attempts to use a linear combination of reservoir responses. Two models of reservoir simulator’s pressure and production response to permeability were presented. These models were derived from the general hyperbolic decline curve. They were used to estimate the permeability
distributions from historical production and pressure information. This history matching technique only requires two or three simulation experiments to accomplish the match.

Yang et al., (2007) presented a systematic history matching approach to condition a reservoir model to production data and quantify the uncertainties of the history matching parameters in terms of probability density functions. The approach utilizes experimental design and multi-objective global optimization techniques. More specifically, for a given list of uncertain parameters, the history matching process is treated as a combinatorial optimization problem to find the best combination of these parameters to achieve the minimum history match error. The combinatorial optimization problem is solved by applying a hybrid meta-heuristic method that combines evolutionary algorithms, Tabu search, and experimental design techniques. The method is successfully applied to the history-matching problem of a complex real reservoir.

Elrafie et al., (2009) presented an innovative history match approach. This approach was developed to enable faster simulation history match under uncertainty, in terms of static and dynamic variables. The history matching process is performed with the aid of assisted history matching software that tracks the match quality of hundreds of history match cases and analyzes the impact of each variable and its range of uncertainty on model match quality to historical field data. Finally, a proxy (statistical History Match solution surface including all uncertainty variables) is created to provide directional guidance to a most likely history match model design. As the history match process progresses, history match variables are characterized into three distinct categories: (1) critical variables to history match, (2) non critical variables to history match but with
significant impact on prediction, and (3) non critical variables to history match but with less impact on prediction. The impact of the variables on prediction is concluded by concurrently running prediction runs under uncertainty. The uncertainty range of the variables categorized in groups (1) and (3) are set to a single realizations or narrower range of uncertainty for each variable while group (2) variables are carried forward with a more restricted range of uncertainty (defined by history match quality analysis) setting the stage for prediction under uncertainty modeling.

Landa and Guyaguler (2003) proposed an approach for automatic history matching based on response surfaces and sensitivity coefficients. The workflow provides a computationally efficient framework for the assessment of the uncertainties associated with prediction. Sensitivity coefficients are used to construct response surface or a proxy for the reservoir simulator model, honoring the exact data values and gradients for the simulated combinations of the parameters. This proxy is then used to guide the selection of the subsequent locations to sample for the history matching process. The accuracy of the proxy increases with the additional simulations as the algorithm progresses. At the end of the history matching process, the proxy is use to estimate the uncertainty associated with the predictions of the future performance of the reservoir model. The proposed method was successfully applied to a synthetic well testing example and a real field case for history matching and uncertainty estimation.
2.2 Overview of Artificial Neural Networks (ANN)

Artificial neural networks (ANN) are mathematical imitations of the biological system. A simple description of an artificial neural network is mapping an input space to an output space (Priddy et al., 2005). A broader definition of ANN is the ability to mimic the nervous system in learning from experience and generalize from previous examples. That process will generate new outputs after learning the characteristics of the inputs (Bailey & Thompson, 1990). The earliest studies involving artificial neural networks can be accredited to McChulloc and Pitts (1943). Rosenblatt (1958) invented the perceptron in 1957 when he developed a pattern-classification task that was able to separate classes. This could be done by training a perceptron to generate a weight vector that separates the classes.

The human brain is extremely complicated system that consists of around $10^{11}$ connected neurons. Each neuron has three main components. These are the dendrites, the cell body or soma, and the axon. The dendrites are receptive networks that carry the electrical signal into the cell body. Processing of these signals then occurs in the cell body. The axon then carries the processed signal to the next neuron. The point that connects the axon of one neuron and the dendrite of another neuron is called the synapse. Most synaptic contacts are of two types: excitatory and inhibitory. An excitatory synapse is a synaptic potential that makes a neuron more likely to generate action potential, while the inhibitory synapse makes a neuron less likely to generate action potential (Purves et al., 2008). Figure 2.3 shows a schematic diagram of two biological neurons.
Figure 2.3: Schematic diagram of two connected neurons. Source: (Hagan et al., 2002)

2.2.1 Artificial Neuron Models

Artificial neural networks are modeled after the nervous system on the basis of the following assumptions (Fausett, 1994):

1- Information is processed in simple elements called neurons.

2- Processed signals are passed between neurons over connecting links.

3- Each connecting link has an associated weight that multiplies the transmitted signal.

4- Each neuron applies an activation function to its input in order to generate an output signal.

Table 2.3 shows the terminological relationship between biological and artificial neurons. An output node is fired when its net input exceeds a certain threshold.

In mathematical terms, the sum of the weighted inputs and biased from the net input signal can be expressed as:
where \( w \) is the weight, \( x \) is the input element, and \( b \) is the bias term. The bias behaves like a weight except that it has a constant input of 1 and it is introduced to shift the activation function to the right or left. Both \( w \) and \( b \) are adjustable scalar parameters of the neuron.

Table 2.3: Terminological relationship between biological and artificial neuron.

<table>
<thead>
<tr>
<th>Biological Neuron</th>
<th>Artificial Neuron</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neuron</td>
<td>Node/Unit/Cell/Neurode</td>
</tr>
<tr>
<td>Synapse</td>
<td>Connection/Edge/Link</td>
</tr>
<tr>
<td>Synaptic Efficiency</td>
<td>Connection Strength/Weight</td>
</tr>
<tr>
<td>Firing Frequency</td>
<td>Node Output</td>
</tr>
</tbody>
</table>

The processed signal is then taken to the output node through a transfer function:

\[
z_k = f(net_k)
\]

where \( z \) is the output signal and \( f \) is the transfer function. Figure 2.4 shows a generic processing element.

Figure 2.4: A generic processing element (neuron). Source: (Priddy et al., 2005)
2.2.2 Transfer Functions

Transfer functions scale the response of a neuron to an external stimulus and then generate the neuron activation (Maren et al., 1990). Transfer functions can be linear or non-linear functions. There are several types of activation functions including:

- The linear transfer function: \( f(x) = x \)  
  \[ (2.5) \]

- The sigmoid transfer function: \( f(x) = \frac{1}{1 + e^{-x}} \)  
  \[ (2.6) \]

- The hyperbolic transfer function: \( f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \)  
  \[ (2.7) \]

- The step transfer function: \( f(x) = \begin{cases} a & \text{if } x < c \\ b & \text{if } x > c \end{cases} \)  
  \[ (2.8) \]

- The linear threshold transfer function: \( f(x) = \begin{cases} x & \text{if } x < c \\ a & \text{if } x > c \end{cases} \)  
  \[ (2.9) \]

Figure 2.5 shows 3 different types of transfer functions: step, sigmoid, and linear in unipolar and bipolar formats.

![Figure 2.5: Popular transfer functions. Source: (Priddy et al., 2005)](image-url)
The linear transfer function or purelin transfer function is usually associated with the output layer since it is possible for the neural network to create its output within the required limits without the need of denormalizing them (Minakowski, 2008). Figure 2.6 shows the purelin transfer function with no bias and when bias is added to the network.

The log-sigmoid and the hyperbolic tangent sigmoid functions are the most commonly applied transfer functions in neural networks, especially when used with multilayer networks that are trained using the back-propagation algorithm. These powerful, continuous, non-linear transfer functions can take any input value and scale it into the range 0 to 1 or -1 to 1. Sigmoid transfer functions have been found to work best in our problem. Ramgulam et al. (2007) also suggested that using sigmoidal transfer functions in the middle layers worked best while dealing with similar reservoir engineering problems. Figure 2.7 shows the log sigmoid transfer function with and without bias.

Figure 2.6: Linear transfer function. Source: (Hagan et al., 2002)

Figure 2.7: Log-sigmoid transfer function. Source: (Hagan et al., 2002)
2.2.3 Network Architectures

Conventionally, a single neuron might not be able to solve many practical problems. Often, multiple neurons operating in parallels are used to form what is called a layer. Networks are mainly classified into three types: single layer feedforward networks, multilayer feedforward networks, and recurrent networks.

2.2.3.1 Single Layer Feedforward Networks:

The layer includes the weight matrix, the summations, the bias vector, the transfer function, and the output vector. Each element of the input vector is connected to each neuron through the weight matrix. Each neuron has a bias, a summation, a transfer function, and an output. Combining the outputs forms the output vector. Many textbooks refer to the processing elements as the hidden layer. It is called hidden because it doesn’t interact with the external surrounding of the network. The feedforward term means that the first layer has a connection from the input vector and each subsequent layer has a connection from the previous layer. Figure 2.8 shows the architecture of a single layer network.

2.2.3.2 Multilayer Feedforward Networks

Multilayer networks consist of several layers connecting the input vector and the output vector. Each layer has its own weight matrix, bias vector, a net input vector, and an output vector (Hagan et al., 2002). Multilayer networks are typically used to solve more complex, non-linear problems that a single layer network has difficulty dealing with. Figure 2.9 shows the architecture of a multilayer network that consists of three layers. In this research, the focus will be on the feedforward networks.
2.2.3.3 Recurrent Networks

Recurrent networks are different than feedforward networks in the sense that they have at least one feedback loop; some of the outputs are connected to the input. The initial conditions are supplied by the input vector. Then, subsequent outputs are calculated from the previous outputs. That means the output is the input delayed by one time step. Figure 2.10 shows an example of a recurrent neural network.
2.2.4 Feedforward Backpropagation Neural Networks

Multilayer feedforward backpropagation neural networks are the most widely used neural networks architecture (Maren et al., 1990). The term backpropagation refers to the backwards propagation of error. Backpropagation is a very common method for training feedforward neural networks, which uses activation functions that are differentiable. To train a neural network, the error calculated method must be determined. The objective of training the network is to minimize this error. The error function must be differentiable. There are several methods for minimizing the error, the most popular of which is the gradient descent method. The algorithm that evaluates the error function derivative is called backpropagation because it propagates the error backward through the network (Heaton, 2008).

2.2.5 Learning Methods

A learning method is a procedure used to modify the connection weights between the nodes and biases of a neural network and learning is the end product of a successful training. There are two broad learning methods: supervised learning and unsupervised learning.
2.2.5.1 Supervised Learning

Supervised learning is a guided training where the network is introduced to the desired response to a given stimulus. The network is presented to the environment, which is represented by a measurement vector. The teacher or guide then determines the desired response. The desired response is then used to generate the error signal that modifies the weights of the network. In essence, each input vector, requires an associated desired output to train the neural network (Priddy et al., 2005). Figure 2.11 shows a schematic diagram of a supervised learning model. In this research, supervised learning models will be used.

Figure 2.11: Block diagram of supervised learning model. Source: (Priddy et al., 2005)

2.2.5.2 Unsupervised Learning Methods

Unsupervised learning is similar to supervised learning except that it doesn’t engage a teacher or guide. The measurement vector is fed to the learning system and a response is generated based the applied adaptation rule. Examples of unsupervised learning techniques include Self-Organizing Maps (SOM) and the Adaptive Resonance Theory (ART) (Priddy et al., 2005). Figure 2.12 shows a schematic diagram of an unsupervised learning model.
2.2.6 Training algorithms

Training algorithms are mathematical functions that are responsible for adjusting the network’s weights and biases. There are several training algorithms such as the gradient descent methods, conjugate gradient methods, the Levenberg-Marquardt (LM) algorithm, and the resilient backpropagation algorithm. In this research, scaled conjugate gradient method and Bayesian regularization methods are utilized.

2.2.6.1 Scaled Conjugate Gradient Method (SCG)

The standard conjugate gradient algorithm requires a line search at each iteration. This operation is computationally expensive and time-consuming. The Scaled conjugate gradient algorithm eliminates the line search requirement. It combines the model-trust region approach that is used by the Levenberg-Marquardt algorithm in order to scale the step size of the conjugate gradient (Møller, 1993). SCG can be used to train any network as long as its weights and transfer functions are differentiable. SCG may require more iterations to converge than other training algorithms, but the iteration is computed significantly faster than other algorithms (Beale et al., 2013).
2.2.6.2 Bayesian Regularization Method (BR)

Bayesian regularization trains the neural network by updating the weights and biases according to the Levenberg-Marquardt method. The LM algorithm attempts to solve a nonlinear least square minimization problem in the form of (Mohamad et al., 2010):

$$f(x) = \frac{1}{2} \|r(x)\|^2$$

(2.10)

where $r$ is the residual vector. Bayesian regularization minimizes a linear combination of squared errors and weights. It also modifies the combination in order to produce a network that can generalize effectively. BR can be used to train any network as long as its weights and transfer functions are differentiable (Beale et al., 2013). Bayesian regularization is computationally quite expensive. Thus it is used less often than the SCG algorithm in this research.

2.2.7 Convergence, Training Efficiency, and Overfitting

When the total error of the current iteration is lower than the previous one then convergence is taking place. Final convergence is attained when the error between the desired and calculated outputs is minimized to a certain threshold. A common convergence method is reducing the mean square:

$$\lim_{n \to \infty} E \{ |x_n - x|^2 \} = 0$$

(2.11)

where $E(x)$ is the estimated value of $x$. One of the problems that prohibits convergence is the local minima on the error surface. To enhance the training efficiency and overcome convergence problems, some techniques can be applied. Introducing a momentum parameter to the steepest descent rule acts as a filter that smoothes the fluctuation in the
descent path due to the local minima (Fausett, 1994). The backpropagation rule is modified by adding the momentum coefficient, $\gamma$, as follows:

$$\Delta w_k(i) = -\alpha \frac{\partial E}{\partial w_k} + \gamma \Delta w_k(i - 1)$$

(2.12)

where $w$ is the weight, $\alpha$ is the learning rate, and $E$ is the error function. The value of the momentum coefficient is $0 \geq \gamma > 1$.

Functional links can also improve training efficiency. These are mathematical functions of inputs or outputs that strengthen the relationships between the parameters. The choice of the number of hidden layers and the number of neurons in each layer has an effect on the convergence speed. Choosing a small number of neurons may lead the network to underperform, while having too many neurons may lead to overfitting.

Overfitting occurs when the error in the training gets very small, but when the network is introduced to new data, the error increases. One way to tackle overfitting is to use a network that is large enough to provide an adequate fit. Unfortunately, there is no easy way to tell if the network size is adequate. Therefore, two common techniques are applied to avoid overfitting and produce good generalization capabilities. These techniques are early stopping and regularization.

To employ early stopping method, the data set is randomly divided into three subsets. The first subset is used for training, that is calculating the gradient and updating the weights and biases. The second subset is the validation set. The error in the validation set is monitored during the training process. Once the error in the validation sets stops to decrease over a preset number of iterations, the training terminates and the weights and
biases at the minimum of the validation error are used. The third subset is the testing data set. It measures the ability of the network to generalize (Beale et al., 2013). This data set is not introduced to the network during the training process. The lower the error in this subset, the better the generalization capability of the network.

Regularization modifies the performance function, which is usually the mean sum of squares of the errors on the training set.

\[ F = mse = \frac{1}{N} \sum_{i=1}^{N} (E_i)^2 = \frac{1}{N} \sum_{i=1}^{N} (t_i - o_i)^2 \]  

where \( N \) is the number of inputs, \( E \) is the error function, \( t \) is the target value, and \( o \) is the output value. The generalization is improved by adding a term that consists of the mean sum of squares of the network’s weights and biases.

\[ msereg = \mu mse + (1-\mu)msw \]  

where \( \mu \) is the performance ratio which has a value between 0 and 1, and

\[ msw = \frac{1}{n} \sum_{j=1}^{n} w_j^2 \]  

Using this performance function will force the network to use smaller weights and biases, causing the network response to be smoother and less likely to overfit (Beale et al., 2013). Both the early stopping and the regularization techniques are implemented throughout this research.

2.2.8 General Uses of Artificial Neural Networks

According to Mehrotra et al., (1997), artificial neural networks can be applied to general fields including:

- Clustering: Grouping objects that share similar properties.
• Vector Quantization: Associating each input sample with the nearest weight vector (with the smallest Euclidian distance).

• Classification: The assignment of each object to a specific class.

• Pattern Recognition: Triggering the generation of a specific output pattern after the presentation of an input sample.

• Function Approximation: Building a function that generates approximately the same output from input vectors as the process being modeled.

• Forecasting: Predicting future events based on past history.

• Optimization: Maximizing or minimizing a function subject to some constraints.

2.2.9 Applications of Artificial Intelligence in the Oil and Gas Industry

The use of artificial intelligence has gained popularity in the oil and gas industry. Artificial Neural Networks (ANNs), in particular, have the benefits of learning, association, real-time capability, self-organization, robustness against noise and generalization (Ali, 1994). ANNs have been successfully utilized in reservoir characterization, virtual magnetic resonance (MR) logs (Mohaghegh, 2000), surface facility modeling (Mohaghegh, 2005), optimization of non-conventional well type location and trajectory (Yeten et al., 2003), relative permeability characteristics (Al-Fattah & Al-Naim, 2009), and designing multilateral well configurations, estimating reservoir properties, and forecasting reservoir performance (Almousa, 2013).

Al-Thuwaini et al., (2006) investigated the application of artificial intelligence to accelerate history matching. Regions of similar trends were created for the reservoir. Self Organizing Maps (SOMs) were used to perform the clustering based on the available
information. The workflow involved the use of production plots and material balance for quality control. Then SOMs were used to evaluate reservoir and well performances in addition to the history match runs.

Doraisamy et al., (1998) applied artificial neural networks in field development strategies. The objective of the study was to maximize oil recovery under some GOR and WOR restrictions. The role of the ANN was to find the optimum well locations that would yield the maximum oil recovery. The two ANN parameters that the study focused on were the learning constant and the number of neurons in the hidden layers. The authors concluded that the use of ANN resulted in satisfactory outcome in terms of field development strategies.

Centilmen et al., (1999) developed an expert system that allows for a rapid and efficient selection of well locations while maintaining reasonable accuracy. In that method, several key well scenarios are selected by engineering judgment and/or randomly. These scenarios are then evaluated using a numerical reservoir simulator. The simulation results form the basis for training an ANN. When the ANN is trained for a specific reservoir configuration, it forms a fast predictive tool for optimizing the locations of the new wells in the reservoir. Thousands of possible scenarios are evaluated using the ANN with an insignificant computational effort. Then, all the predictions are ranked and sorted to provide the best possible scenario for placing the new wells. It is the combination between ANN and genetic concepts that leads to an efficient optimization process.
Ramgulam et al., (2007) provided a guideline to develop and train artificial neural networks to predict certain reservoir properties in order to improve history matching. The authors considered the following factors to be instrumental in achieving a good architecture for training the ANN: data structure, number of hidden layers and their neurons, transfer function, training algorithm, functional links, and performance functions. Cases with different levels of heterogeneity, number of wells, and number of regions were tested. ANN was able to reduce the number of simulation runs needed to achieve a history match.

Minakowski (2008) developed two neuro-simulation tools for screening and designing miscible injection, water flooding and steam injection processes. The tools help narrow the ranges of possible scenarios to be modeled using conventional reservoir simulation, reducing the potentially extensive time and energy spent in modeling these studies. The results of the study show that the networks are able to recognize the strong correlation between the displacement mechanism and the reservoir characteristics as they effectively forecast hydrocarbon performance for different reservoir types undergoing diverse recovery processes.

Chidambaram (2009) developed and tested an artificial neural network based history matching protocol to characterize reservoir properties. He developed a neural network tool that predicted the parameters required to build the reservoir model. A lot of trial and error was involved before history matching was achieved. This method eliminated the need of initial guesses of the properties. As the complexity of the problem increases, the network parameters needed to be revisited and the functional links needed
to be varied. This method was successfully applied to a reservoir that was divided into four regions and had 18 producing wells.

Bansal (2011) developed an expert system that can characterize tight oil reservoirs. The system can suggest completion parameters and predict quarterly cumulative production of oil, water, and gas for a two-year period. Ultimately, the expert system can suggest the best infill drilling location in the field with a forecast of their respective cumulative production by the end of two years. The performance of the expert system has been in good agreement with the actual data coming from the field.

Almousa (2013) developed a set of integrated artificial expert systems in the area of forecasting, reservoir evaluation and multilateral well design. The tools covered single gas phase reservoirs with dual-laterals and multi-laterals with different reservoir properties. One tool was applied to a bottom water drive system completed with multilateral of 2 to 5 branches. The developed approach successfully delivers a total of five distinct artificial expert systems, three of which 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.

Gonzalez et al., (2012) developed an expert system to predict wells’ production performance after a polymer gel treatment for water shutoff. A total of 31 historical sample applications of gel treatments were used for training and validating the proposed networks. Historical applications gathered include different well and reservoir types, which make the model prediction validity wide broad.
Neural networks with two different tasks were developed during the study, one of them with a bi-valuated response (output), and qualified as classification networks and the other with a wider range of potential output, identified as regression networks. The model aims to predict a well future oil production and the percentage of water associated to that production after the execution of a gel treatment. The proposed neural networks allow the selection of future candidate wells for gel treatments, based on its potential success. Additionally, the proposed network allows improving future gel treatments by evaluating the effect of the volume of gel to be injected on the treatment’s result.

Ayala and Ertekin (2007) developed a neuro-simulation tool for the analysis of gas cycling operations in gas condensate reservoirs. The neuro-simulation approach combines a back-propagation ANN with a compositional reservoir simulator. This work has presented four artificial neural networks developed as gas cycling performance predictors for operations taking place in gas condensate reservoirs. Analysis of the performance of the ANN models shows an excellent agreement with the prediction of the compositional simulator, based on the results of all cross-plot and absolute error analyses. Once the ANN is trained, the prediction of gas cycling performance involves highly accurate and fast calculations. It is also demonstrated that ANN models can perform predictions that could prove tremendously cumbersome to replicate using a traditional compositional simulator. Case studies provided in this paper indicate that neuro-simulation has the potential of dramatically improving the capabilities of reservoir engineers to design optimum production schemes to be used in the exploitation of gas condensate fields.
Cullick et al., (2006) presented two workflows for assisted history matching. One workflow minimizes the misfit between simulated and observed data with a global optimizer by adjusting reservoir and well unknown parameters. The second workflow is used to reduce the number of numerical simulations. The workflow trains a comprehensive nonlinear proxy model with a small set of numerical simulations from experimental design. The nonlinear proxy neural network is used to characterize parameter sensitivities to reservoir parameters and to generate solution sets of the parameters that match history. The neural network solution sets can be validated with the simulator or used as initial solutions for a full optimization. The authors concluded that the two workflows were robust nonlinear proxy models that were quite efficient as compared with the conventional manual history matching process.

2.3 Well and Reservoir Problems

There are several factors that can affect the well performance. The most frequent occurrences of well problems are grouped into the following general classifications: the reservoir, the wellbore, and the completion. Reservoirs are highly complex geological structures, which must be effectively managed to produce optimally. There are several reasons why reservoirs may generate problems:

1. Initially, reservoirs are developed with limited data and hence an incomplete understanding of their physical characteristics. Therefore, they are modeled with limited accuracy.

2. Reservoirs exhibit a dynamic response to production and injection. This implies that they need periodical updating and evaluation since they become outdated quite often.
3. Production equipment has a finite working life, which depends on its application and the way it is installed.

### 2.3.1 Productivity/Injectivity Problems

The performance of the reservoir depends on how optimal the utilization of reservoir pressure is. Perforation characteristics can play a role in hindering the well’s productivity or injectivity. Shot phasing, shot density, diameter and length of perforations, perforation damage due to compaction and filtration, and formation anisotropy are factors that can control the well’s productivity. There are many other factors that can affect the deliverability of the reservoir. The simplest mathematical relationship that defines the productivity of a well is the steady state radial flow equation:

\[
P_e - P_{wf} = 141.2 \frac{q_s \mu_s B_s}{k_s h} \ln \frac{r_e}{r_w}
\]

(2.16)

where \(P_e\) is the external pressure, \(P_{wf}\) is the flowing bottomhole pressure, \(q\) is the flow rate, \(\mu\) is the fluid viscosity, \(B\) is the formation volume factor, \(k\) is the permeability of rock to fluid \(s\), \(r\) is the radius, and \(h\) is the reservoir thickness. Subscripts \(e\) refers to the outer radius of the reservoir, \(wf\) is the bottom hole pressure, \(w\) is the wellbore, \(s\) is the fluid phase. As it can be inferred, the fluid flow from the reservoir towards the wellbore is controlled by the reservoir pressure, reservoir size and its ability to maintain pressure, reservoir fluid mobility \(k/\mu\), and reservoir thickness.

### 2.3.2 Formation Damage

Well Performance can be altered at any stage of the well development from the initial drilling through to production and workover. These factors that limit the well
performance are referred to as formation damage and their effect is to reduce the productivity by one or more of the following:

- Reduce the absolute permeability of the rock.
- Reduce the relative permeability of the system.
- Increase the mobile fluid viscosity.

Formation damage can occur because of several reasons, including:

- Plugging of the pore space by solid particles
- Scale deposition
- Clay swelling
- Compaction associated with reservoir depletion
- Changes in wettability
- Modification to fluid saturation
- Emulsion formation (Somerville, 2004)

2.3.2.1 Skin

The near wellbore permeability could be reduced by formation damage caused by mud filtrate invasion. On the other hand, if the well is treated by an acid job, its near wellbore permeability is enhanced. Thus, for a damaged or stimulated well, there is a region of altered permeability near the wellbore (Peters, 2009). Figure 2.13 shows the effect of skin on well inflow pressure profile.
The additional pressure change near the wellbore caused by the region of altered permeability can be incorporated into the well test model through the concept of skin factor. The skin factor, $S$, is a dimensionless pressure change at the wellbore:

$$ P_e - S = \frac{\Delta P_{\text{skin}}}{141.2 \left( \frac{q \mu B}{k h} \right)} $$  \hspace{1cm} (2.17)

where

$$ \Delta P_{\text{skin}} = P_{\text{wf unaltered}} - P_{\text{wf altered}} $$ \hspace{1cm} (2.18)

Hence, $S$ is positive for a damaged well and negative for a stimulated well.

Skin can be determined by a well test. This is the total skin, which incorporates several components.

$$ S_{\text{total}} = S_{\text{damage}} + S_{\text{geometry}} + S_{\text{completion}} + S_{\text{production}} $$ \hspace{1cm} (2.19)

Geometrical skin arises from several factors including:

- Limited entry: well not perforated across the complete reservoir height and/or well not fully penetrating the reservoir.
- Well not placed in the center of the drainage boundary.
• Well is slanted through the formation causing it to have a longer exposure which results in a negative skin.

Completion skin may result from low perforation density, too short or too narrow shape, or incorrect phasing. Gravel packing usually causes a positive skin. Fractures, either naturally or artificially, will lead to a negative skin. Examples of production skins are:

• A rate dependent skin that is observed in high rate gas wells. The turbulent, non-Darcy flow causes this type of skin.

• A flowing bottom hole pressure below the bubble point in an oil well.

• A retrograde condensate fluid where there is a two-phase flow region at the perforation (Somerville, 2005).

2.4 Reservoir Compaction

Compaction is the process in which the compressive strength of the rock is exceeded and plastic deformation occurs. This results in irreversible reduction of porosity and permeability. Besides providing the additional drive energy for production, it has important consequences both inside and outside the reservoir. The most obvious impact is the surface deformation, which creates problems the environment and field structure. Additional mechanisms that can induce compaction include shear failure and increase in temperature (Settari, 2002). Permeability also decreases with increasing stresses. Davis and Davis (1999) described compaction as stress-related physical changes due to grain slippage, grain rotation, ductile changes in grain shape, and grain fracturing. These processes result in a decreased pore volume and pore throat, which in turn means lower porosity and permeability.
In unconsolidated porous media, a process called dilation can take place. Shear failure can be reached more easily, especially around the wellbore, because of the low frictional strength at small effective stresses. This process causes less compact grain arrangement whereby porosity actually increases with increased load, which is opposite to compaction (Settari, 2002).

2.5 Hydraulic Well Fracturing

Propped hydraulic fracturing involves pumping a viscous fluid at a sufficiently high pressure into the completion interval so that a two winged, hydraulic fracture is formed. The fracture is then filled with a high conductivity proppant that holds the fracture open. The hydraulic fracture can have width between 5mm and 35mm and a length of 100m or more, depending on the design technique and the size of the treatment. The objective of hydraulic fracturing is to increase the effective wellbore radius for wells completed in low permeability formations. The radial flow equation is:

\[
Q = \frac{kh(P_e - P_{wf})}{141.2 \mu B_o \left\{ln\left(\frac{r_e}{r_w}\right)+S\right\}} = \frac{kh(P_e - P_{wf})}{141.2 \mu B_o \ln\left(\frac{r_e}{r_{w_e}}\right)} \tag{2.20}
\]

The above equation implies that the well production rate can be increased by:

- Increasing the flow capacity (k.h), where the fracture may connect to a higher permeability zone
- Bypassing the damaged zone
- Increasing the wellbore radius (r_w) to an effective well bore radius (r_{w_e}), where r_{w_e} is a function of the conductive fracture length L_c. Figure 2.14 shows a schematic diagram of hydraulic fracture geometry.
If the hydraulic fracture has infinite conductivity, i.e., there is a negligible pressure drop along the length of the fracture, then:

\[ r_w' = \frac{L_f}{2} \]  \hspace{1cm} (2.21)

High conductivity fractures allow fluids to flow to the well with an effective wellbore radius that is equal to half the single wing fracture length (Somerville, 2005).

![Diagram of hydraulic fracture](image)

**Figure 2.14:** Geometry of a hydraulic fracture. Source: (Somerville, 2005)

According to Daneshy (2010), Radial flow from the reservoir, especially at low permeability, into the wellbore is not very efficient. As fluid approaches the wellbore, it has to pass through successively smaller areas causing “jamming” of the fluid. Hydraulic fractures transform this flow profile into a nearly linear flow regime. Figure 2.15 shows a comparison between the two flow systems.
Hydraulic fracture efficiency can be measured by the non-dimensional conductivity, which is defined by:

$$C_D = \frac{k_f w_f}{k_m L_f}$$  \hspace{1cm} (2.22)

where $k_f$ is the fracture permeability, $k_m$ is the matrix permeability, $w_f$ is the fracture width, and $L_f$ is the fracture half length. A reasonable range for non-dimensional conductivity is $1 < C_D < 10$.

### 2.5.1 Reasons for Hydraulic Fracturing

Hydraulic fracturing can bypass the damaged zone near the wellbore and lessen its negative effect on production. In formations with potential sand production, hydraulic fracturing can restrict sand production by allowing the well to produce at a higher bottom-hole pressure. Hydraulic fracturing can also increase the ultimate recovery factor of the reservoir that corresponds to the economic cutoff of production. For these and other reasons, hydraulic fracturing is one of the most common completion in the oil and gas industry (Daneshy, 2010). 

Figure 2.15: Radial flow and linear flow after hydraulic fracturing.

Source: (Daneshy, 2010)
2.5.2 Mechanics of Hydraulic Fracturing

An initial fracture of appropriate length and width is created by pumping fracture fluid. During fluid injection, the fluid pressure inside the fracture is higher than the least in-situ principal stress, and this keeps the fracture open. After the injection stops and pressure is allowed to drop, the fracture begins to close. To keep the fracture open and conductive (permeable) after the treatment, a proppant is mixed with the fluid and injected inside the fracture to keep it open during production operations.

Fracturing materials consists of the fluid and proppant. The most common fracturing fluid is a mixture of water and additives such as polymer-based viscosifiers, friction reducers, breakers, clay stabilizers, and surfactants. The most common proppant is natural sand that meets a certain specification requirements. The proppant is carried far along the fractures by the viscous fluid which might have a viscosity ranging from a few tens to several thousands centipoises. The fracture itself is characterized by its length, width and height (Daneshy, 2010). Figure 2.16 illustrates the relative dimensions of a hydraulic fracture relative to the wellbore.

![Figure 2.16: Dimensions of a hydraulic fracture relative to the wellbore. Source: (Daneshy, 2010)](image.png)
2.6 Tarmat

Tarmat or heavy oil at the base of the hydrocarbon column is common in many reservoirs in the Middle East (Acharya, 1987). Tarmat is usually present at the oil-water contact, forming sealing barriers that isolate the reservoirs from their aquifers. Some of these tarmats are mobile under conditions of moderate differential pressure across them and others are immobile. The pressure differential across the tarmat can be caused by oil production from the reservoir and injection below the tarmat (Osman, 1988). Geomechanical studies indicate that tarmats could have formed as a result of:

- Gravitational segregation that caused the hydrocarbon fractions to stratify with the lighter petroleum at the top of the reservoir and the heavier at the base.
- Natural deasphalting where natural, buoyant gases from the source rock entered the pool and rose through the hydrocarbon column, lowering the solubility of the asphaltic fraction, which would consequently precipitate and fall to the base of the reservoir
- Water washing, which is the removal of the more water soluble components from a hydrocarbon accumulation, leaving asphaltic fractions at the base of oil column (Osman, 1985).

Sometimes, the tarmat layer is intentionally broken. The breakdown serves two purposes: to recover some of the tarmat (heavy oil) and to increase the communication between the reservoir and its aquifer thus use aquifer’s energy to produce more oil (Osman, 1988). However, it is difficult to predict the time and location where the breakdown occurs. Nonetheless, there exist some geomechanical and mathematical
models that can help. Figure 2.17 is a cross section of a typical reservoir with the tarmat at the bottom of the oil zone.

![Figure 2.17: A cross section of a reservoir with tarmat. Source: (Tripathy, 1988)](image)

2.6.1 Tarmat Modeling

There are two general approaches to modeling tarmat within a hydrocarbon reservoir. The first one is to model the tarmat as part of aquifer rock matrix and the other is to model as part of the reservoir fluid system. Figure 2.18 shows a schematic diagram of the two approaches.

![Figure 2.18: Modeling tarmat as part of the aquifer (left) and as part of the hydrocarbon fluid (right). Source: (Tripathy, 1988)](image)
When modeling the tarmat as part of the aquifer rock, the model’s oil-water contact is placed at the top of the tar zone. The very low permeability of the tar cells acts as a barrier between the aquifer and the oil zone. The physical process of breaking the tarmat cannot be duplicated by the model. The workaround for this limitation is to assign a separate permeability region for the broken tarmat cells with reduced relative permeability to water. This provides aquifer support to the oil column in the case of a leaking tarmat. This modeling approach is going to be applied in this research.

When modeling the tarmat as part of the reservoir fluid system, the tar is modeled as a highly viscous reservoir fluid. Several PVT zones are assigned where viscosity increases as the depth increase. Under this technique, the tar-containing rock matrix is assigned the same relative permeability and capillary pressure curves that strictly apply to the oil-zone rock. The assumption is valid where mobility is strongly influenced by the high viscosity. In this event, the capillary curve exhibits a transition zone and assignment of such a curve to the tarmat establishes a movable water saturation across the tar zone. This in turn creates a link between the aquifer and the oil column with the use of a favorable relative permeability curve (Tripathy, 1988).

2.6.2 Rock Mechanics

Rock mechanics is a theoretical and applied science that deals with the behavior of rocks. It is a branch of mechanics concerned with the response of rocks to the force fields of its physical environment (Cook et al., 1966).
2.6.2.1 Stress and Strain

The understanding of the stress and strain relationship is relevant to the tarmat breakdown process. A simple definition of stress is a distributed force on an external or internal surface of a body. In other words, stress is the ratio of applied force (tensile or compressive) and cross section, defined as force per area. Stresses are classified into normal stresses and shear stresses. Stress normal to the plane is referred to as normal stress, while stress parallel to the plane is referred to as shear stress. Strain is defined as the deformation of a solid due to stress. It can also be expressed as the ratio of elongation with respect to the original length. Strain associated with normal stress is normal strain where strain associated with shear stress is shear strain. An important concept about stress is the principle stresses. These stresses are defined as maximum and minimum normal stresses. Principle stresses are associated both with normal stresses and shear stresses.

2.6.2.2 Material Properties of the Rocks

Other important rock properties that are relevant to the work of this research include Young’s modulus of elasticity, Poisson’s ration, and strength. Young’s modulus of elasticity characterizes the stiffness of the rock, in other words its resistance to an axial stress (Nauroy, 2011). It is a constant of proportionality that is a function of axial stress, $\sigma$, and the axial strain, $\varepsilon$, and can be expressed as:

$$E = \frac{\sigma}{\varepsilon}$$  \hspace{1cm} (2.23)

Poisson’s ratio is a dimensionless quantity that relates lateral strain and axial strain:

$$\nu = -\frac{\varepsilon_x}{\varepsilon_z}$$  \hspace{1cm} (2.24)
The negative sign denotes that the lateral strain and axial strain has opposite signs. Strength of the rock is another important rock property. There are several types of rock strengths:

- **Yield strength** is the lowest stress that produces a permanent deformation in a material.
- **Tensile strength** is a limit state of tensile stress that leads to tensile failure in the manner of ductile failure.
- **Compressive strength** is a limit state of compressive stress that leads to failure in a material in the manner of ductile failure.
- **Fatigue strength** is a measure of the strength of a material or a component under cyclic loading.
- **Impact strength** is the capability of the material to withstand a suddenly applied load and is expressed in terms of energy (Beer et al., 2009).

### 2.7 Naturally Fractured Reservoirs

Naturally fractured reservoirs play an important source of hydrocarbon production around the world (Nelson, 2001). There is an interconnected system of fracture planes within the porous rocks, which are called the matrix. In this type of reservoirs, hydrocarbons are stored in the rock matrix, which typically has very low permeability. The natural fracture system is the main contributor to the hydrocarbon production. The hydrocarbon fluid moves very slowly within the matrix and when it enters the fracture system, it flows relatively fast, since the fracture system has a much higher permeability. Natural fractures can be characterized by well testing and logging. However, due to the tight matrix permeability, well test data is affected by the wellbore storage effect that
masks the reservoir response to pressure changes and hence cannot provide appropriate
description of the fracture permeability, storativity ratio, and inter-porosity flow
coefficient (Bahrami et al., 2012). In order to model reservoirs with natural fractures,
dual-porosity models are utilized.

2.7.1 Classification of Naturally Fractured Reservoirs

Naturally fractured reservoirs are classified based on the effect the fracture system
provides to overall reservoir quality. Hubbert and Willis (1955) defined naturally
fractured reservoirs as those from which production of hydrocarbons would not occur, or
else would be seriously reduced. These reservoirs fall into two main classes. The first
type is where the reservoir matrix has negligible porosity and the fractures provide both
the porosity and permeability. The second type is where the reservoir has adequate
porosity and the fractures provide the essential permeability.

A new expansion to the above classification suggests four types of naturally fractured
reservoirs (Nelson, 2001):

1. Fractures provide the essential reservoir porosity and permeability.
2. Fractures provide the essential reservoir permeability.
3. Fractures assist permeability in an already producible reservoir.
4. Fractures provide no additional porosity or permeability but create significant
   reservoir anisotropy.

Figure 2.19 shows a cross plot of percent reservoir porosity versus percent reservoir
permeability for the four-type fractured reservoir classification.
2.7.2 Dual Porosity Reservoir Simulation Models

Dual porosity reservoir simulation models are used to simulate naturally fractured reservoirs. In these models, the reservoir is discretized into two porous media (two sets of grid blocks located in the same space), one called the matrix and the other called the fracture. The matrix medium is comprised of matrix blocks that are separated spatially by fractures. The fracture characteristics are described by the fracture spacing, orientation and width. Computationally, fracture transfer is modeled by a single flow term (Computer Modelling Group Ltd, 2011). Since there are two media in the dual porosity systems, it is mandatory to define both the matrix and fracture flow at each point of the matrix.

The most common geometrical representations of a natural fracture system are the models developed by Warren-Root and Gilman-Kazemi as shown in figure 2.19.
The main parameters that affect the flow in natural fractures are the inter-porosity flow coefficient ($\lambda$) and fracture soraritivity ratio ($\omega$) that are defined as follows:

\[
\lambda = \delta \frac{K_m}{K_f} r_w^2
\]  \hspace{1cm} (2.25)

\[
\omega = \frac{\phi_f C_f}{\phi_f C_f + \phi_m C_m}
\]  \hspace{1cm} (2.26)

where $K_m$ is the matrix permeability, $K_f$ is the fracture permeability, $r_w$ is the wellbore radius, $\phi_f$ is the fracture porosity, $\phi_m$ is the matrix porosity, $C_f$ is the fracture compressibility, $C_m$ is the matrix compressibility, and $\delta$ is the shape factor which is defined as follows:

\[
\delta = 4 \left( \frac{1}{L_x^2} + \frac{1}{L_y^2} + \frac{1}{L_z^2} \right)
\]  \hspace{1cm} (2.27)

where $L$ is the cubical matrix block dimension in different axes. The smaller value of $\lambda$ (higher fracture permeability and/or the larger value of $\omega$ (higher fracture porosity) result in higher well productivity (Bahrami et al., 2012).
2.7.3 Basic Parameters of Fractures

Basic parameters of fractures can be divided into two categories. The first is the single fracture parameters such as width, size and nature of fracture. Multi-fracture parameters refer to the fracture geometry, distribution and density. Some fracture parameters pertaining to this research will be discussed.

The fracture width or opening is represented by the distance between the fracture walls. The fracture opening varies between 10-200 microns, but statistically the most frequent range is between 10-40 microns. Figure 2.21 shows the statistical frequency of natural fracture widths in microns.

![Figure 2.21: Fracture width frequency. Source: (Golf-Racht, 1982)](image)

Fracture spacing represents the length of the matrix between two consecutive fractures. The less the fracture spacing is, the higher the well productivity. Fracture porosity refers to the ratio of fracture void volume to the total bulk volume. A typical range of fracture porosity is between 0.01-2% (Golf-Racht, 1982). Fracture permeability for a single fracture can be approximated by $b^3/12$, where $b$ is the fracture width. Relative permeability curves for fractures are difficult to obtain. Therefore, it is usually assumed
that the flow is a piston-like displacement where the relative permeability is equal to the phase saturation (Gilman & Kazemi, 1983). Figure 2.22 shows typical relative permeability curves for matrix and fractures.

Figure 2.22: Relative permeability curves. Source: (Gilman & Kazemi, 1983)
Chapter 3 Problem Statement

With the wealth of data available from conventional wells in general and smart wells in particular, it is only natural to extend efforts to extract the most information out of it. It is in the utmost interest of an oil company to reduce uncertainties and maximize oil recovery. Since many reservoir engineering studies involve the use of reservoir simulators, creating a reliable history matched model that can perform accurate predictions is essential. Several studies suggested different techniques to automate the history matching process. However, many of these techniques can dangerously eliminate the involvement of the reservoir engineer’s judgment and knowledge from the reservoir (Ertekin et al., 2001). The use of expert systems has gained some ground in automated history matching since Chidambaram (2009) and Ramgulam et al., (2007) have developed workflows to predict reservoir properties in order to achieve a good quality history match. However, these studies were limited in the number of uncertain parameters considered and they did not adequately address how the prediction performance would be enhanced by the correct identification of the reservoir properties.

In this study, the direct involvement of the reservoir engineer is shown to be the main contribution to the success of the history matching process. The reservoir engineer is responsible for estimating the range of uncertainty of each reservoir parameter that needs to be altered for the history match. A commercial reservoir simulation software package is used to generate the required data to perform the history matching process. Since artificial neural networks have the ability to generalize, they are used to find a satisfactory set of outputs from the input data set that is not used during training. The first developed tool is the neural network forward solution. This tool is to be used as a proxy
model to the full reservoir simulation model. After that, the inverse solution tool is used to specify a history matching starting point for a newly created reservoir simulation model or to fine-tune the reservoir parameters for an already history matched model.

The proposed study can accommodate complex cases with several uncertain parameters. History matching starting points are obtained as outlined above. Once the new production data is available, it can be incorporated in the neural network to enhance the quality of the history match. The outcome will try to be as close to the real reservoir values as possible instead of just getting a non-unique history matching parameter combination.

Once a satisfactory history match is achieved, additional tools are built to accommodate the dynamic changes that affect production behavior. With the collaboration of geoscientists and reservoir engineers, the deduced input is translated into an expert system that can be utilized as a package of diagnostic tools to pinpoint the causes of the production decline. The first tool checks if the cause of the decline could be due developed skin around the well or if a set of perforation is plugged. Another tool studies the reservoir compaction mechanism and determines if the cause of unexpected production behavior is because of the reduced porosity and permeability as a result of the compaction. One more tool is developed to characterize the hydraulic fractures. This tool can approximate the length and effective permeability of the hydraulic fractures if the production profile is different than what is expected. The last tool will be applied to reservoirs that have tarmat at the base of hydrocarbon column. Its purpose is to determine whether that tarmat has broken as a result of increasing differential pressure across the tarmat layer. Unexpected water breakthrough, increase in bottom-hole pressure, or
increase in the oil rate could be a signal of the tar mat breakdown. The tool will aim to find the approximate location of the breakage and the time it occurs.

The knowledge gained from these expert system tools will help reservoir engineers tackle reservoir problems in an efficient manner and can also serve as cost-effective techniques by eliminating extra well tests and logs. The results should also be incorporated back into the reservoir simulation model to keep the history match up-to-date. The proposed study represents an ambitious effort to develop a workflow that starts from the day the reservoir simulation model is created and continues as long as the reservoir is in production.
Chapter 4 Methodology

This chapter summarizes the applied workflow starting from the base case reservoir simulation model to the developed artificial expert systems. These systems will be used for fine-tuning the reservoir parameters that are fed to the numerical model and for the various parts that are concerned with the diagnosis of the unexpected reservoir behavior.

4.1 The Starting Point

The concept demonstration starts with a simple form of the case investigated. The workflow is then applied to that case to make sure that the results are satisfactory. Starting simply helps pave the way to dealing with more complex scenarios. It is of great importance to understand the behavior of the reservoir during its lifetime and have a sense of the required parameters to successfully train the neural network.

4.2 Reservoir Simulation Model

All cases start with synthetic examples generated by the numerical reservoir simulation. Developed by Computer Modeling Group (CMG), a black oil simulator (IMEX™) and a compositional simulator (SGEMS™) are used. The simulators run all the scenarios that are present in the dataset. Since there are hundreds of cases to run each time, a piece of software called CMOST™ is used to coordinates the run. CMOST generates the datasets by using Monte Carlo sampling technique for the different parameters provided by the user. A user is required to input a range for the reservoir parameters to be varied and then CMOST samples from these parameters. The data is then extracted and formatted to be used with the artificial neural network training.

1. CMG: Computer Modeling Group, a registered trademark for computer Modeling Group Ltd.
2. IMEX™ is a commercial three-phase black oil reservoir simulator developed by CMG®.
3. GEM™ is a commercial compositional reservoir simulator developed by CMG®.
4. CMOST™ is a sensitivity analysis, history matching, optimization, and risk analysis tool developed by CMG®.
4.3 Artificial Neural Network Design

This section summarizes the steps involved in building an artificial neural network expert system presented in this research.

4.3.1 Data Preparation

The output from the reservoir simulation is processed for use with the artificial neural network. The data is usually normalized between -1 and 1 to reduce the variation in the parameter values. This will simplify the neural network training and hence improve the overall performance of the network. Another common data transformation that is applied to the data is the logarithmic transformation. Permeability is a good example to which the logarithmic transformation is applied since the permeability range is very wide.

Functional links are sometimes used to facilitate network training. Functional links are mathematical functions of the inputs or outputs that can strengthen the relationship between the parameters. However, there is no rule about deciding which functional link to use. Trial and error is the typical path to follow to determine which functional links help the network performance. Sometimes, using functional links can have detrimental effects on the network performance and hence their use is discouraged in this case.

The data is then randomly divided into three subsets: one for training, one for validation, and one for testing. The percentages among these subsets are 75%, 15%, and 10%, respectively.
4.3.2 Training Algorithm

Matlab® is used to run the neural network training algorithm through the feedforward backpropagation network. Most of the training is done using the scaled conjugate gradient (SCG). After many trials, SCG proved to give the least error with reasonably fast convergence. The learning function associated with it “learngdm”, which is a gradient descent with momentum weight and bias learning function. The performance function is the mean sum of squares with regularization “msereg”. In the case of very non-linear problems, SCG fails to produce an output with acceptable errors. Hence, the Bayesian regularization (BR) training algorithm is used. BR generates output with less error, but it takes much longer time to train. This algorithm uses “learngdm” as the learning function and the mean sum of squares “mse” as the performance function. The performance function doesn’t need to have regularization since the training algorithm itself uses regularization.

The transfer functions used are the sigmoidal functions. These prove to be more effective in dealing with the problems addressed in this research. Both the hyperbolic tangent sigmoid transfer function “tansig” and the log-sigmoid transfer function “logsig” are used in all network trainings.

4.3.3 Number of Neurons

There is no set rule of how many hidden layers to use and how many neurons in each layer. Most of the problems can be solved with one hidden layer. More complex problems may require two hidden layers in order to converge with low error. Literature reports the use of up to 5 hidden layers, but only one or two layers are used in this

1. MATLAB is a numerical computing environment and a programming language.
research. Although neurons in the hidden layers do not interact with the external environment, they have a remarkable influence on the final output. Using too few neurons in the hidden layers can result in underfitting, which means the network will fail to detect the relationship between the input and output. On the other hand, using too many neurons can result in overfitting where the network memorizes the training data and fail to generalize by getting high errors in the testing dataset. If the network requires too many neurons, it will need more time to train. There are many rule-of-thumb methods for determining the adequate number of neurons in the hidden layers, such as:

- The number of hidden neurons should be between the number of input and output parameters.
- The number of hidden neurons should be $2/3$ the size of the input layer plus the size of the output layer.
- The number of hidden layers should less than twice the size of the input layer (Heaton, 2008).

These rules can be applied as a starting point for choosing the number of neurons. Still, trial and error is the ultimate method to determine the number of neurons in the hidden layers. The method used here is to train the network several times with different number of neurons. The network with the least errors in the testing data subset is then used.

4.3.4 Error reporting

Since the training process is repeated many times with different number of neurons, it is important to know which network produced the least error in the testing data subset. What is meant by error here is how different is the simulated data subset from the actual
input values. Different error calculations are used depending on the nature of the problem. Here are a few error functions used in this research:

- Average absolute difference: \( \frac{1}{n} \sum_{i=1}^{n} |ANN - Observed| \)

- Average percentage error: \( \frac{1}{n} \sum_{i=1}^{n} \frac{|ANN - Observed|}{Observed} \times 100 \)

- Average percentage relative error: \( \frac{1}{n} \sum_{i=1}^{n} \frac{ANN - Observed}{\max(Observed) - \min(\text{observed})} \times 100 \)

- Normalized root mean square:

\[
\sqrt{\frac{\sum_{i=1}^{n} (ANN - Observed)^2}{n}} \div \sqrt{\frac{\sum_{i=1}^{n} (\max(Observed) - \min(\text{observed}))^2}{n}}
\]

- Pearson Correlation coefficient, R:

\[
\frac{\text{cov}(ANN,\text{Observed})}{\sigma_{ANN} \sigma_{\text{Observed}}}
\]

- Coefficient of determination, R\(^2\):

\[
\frac{\sum(ANN - \text{mean(Observed)})^2}{\sum(\text{Observed} - \text{mean(Observed)})^2}
\]

### 4.4 Proceeding with the Solution

Training the neural network for a certain problem is done over two phases. The first one is the forward solution, where the reservoir properties serve as the input to the network and the well production profiles serve as the output. The forward solution can function as a proxy to the reservoir simulation model. If trained properly, the forward solution can be reliable and fast. Tedious tasks done with the numerical simulation such as sensitivity analysis studies can be done much faster when using neural networks.

The second phase is the backward solution, where the well production profiles serve as the input to the network and the reservoir properties serve as the output. The backward solution is the ultimate objective of each case study. Since the well production
profiles such as oil, water and gas rates, and pressures are measured at the surface and thus known, it is the question of knowing what’s under the ground that causes such production behavior. After the successful training of a backward neural network, it can be used as a powerful tool that can predict uncertain parameters in the reservoir.

The results from the backward solution can be validated by the high-fidelity numerical reservoir simulator. The network output is fed to the reservoir simulator whose output is then compared with the observed production profile. If the results are close enough then the network’s generalization capability is trusted. If there are discrepancies between the results, then the network may need to be retrained.
Chapter 5 Reservoir Properties Determination:
An Assisted History Matching Approach

This chapter describes how a reservoir simulation engineer can utilize expert systems to reduce the uncertainties in the reservoir parameters that are used for history matching. The starting point is a reservoir simulation model that is geologically well characterized. The engineer is then required to list the uncertain parameters with their uncertainty range. Sensitivity analysis can be performed to eliminate the parameters that have limited effect on the reservoir performance. The reservoir simulation model will be used to generate the required data to feed the expert system. The output from the neural network can provide starting points for history matching. Moreover, the expert system can return fine-tuned reservoir properties. This will reduce the uncertainty in the reservoir properties so that further field development can be planned more efficiently.

5.1 Base Case: 5 Uncertain Parameters

To demonstrate the concept, a simple single-phase, homogeneous oil reservoir is constructed. The reservoir is a square-shaped reservoir and has constant porosity and horizontal permeability. The reservoir model is structured as a 29x29x8-block model. The vertical permeability is 10% of the lateral permeability. The reservoir is depleted by five vertical wells: one in the center which is completed from the top of the formation to the midpoint of layer 3, and four additional wells symmetrically placed on the sides and are completed to layer 2. There exists a strong water aquifer in the bottom, which is modeled by Carter-Tracy’s method. The top of the reservoir is at 5000’. The oil-water
contact (OWC) is located at the top of layer 7 at 5150’. Figure 5.1 is a schematic of the reservoir and its initial water saturation distribution.

There are five uncertain parameters in this reservoir. These are the original oil water contact, porosity, horizontal permeability, vertical to horizontal permeability ratio ($k_v/k_h$), and the geometric factor (partial completion) of well 1 in layer 3. In order to build the artificial neural network for these unknowns, CMOST™*, a software package in the commercial reservoir simulation suite, is utilized to generate the required data using Latin hypercube sampling method in the history matching module. Table 5.1 shows the 5 uncertain parameters with their range of uncertainty.

![Figure 5.1: Reservoir initial water saturation](image)

Figure 5.1: Reservoir initial water saturation
Table-5.1: Ranges of the uncertain parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Unit</th>
<th>Range</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>OOWC</td>
<td>ft</td>
<td>5100 - 5180</td>
<td>Original oil water contact</td>
</tr>
<tr>
<td>φ</td>
<td>Dimensionless</td>
<td>0.2 – 0.3</td>
<td>Porosity</td>
</tr>
<tr>
<td>k</td>
<td>md</td>
<td>50 – 150</td>
<td>Horizontal permeability</td>
</tr>
<tr>
<td>k_v/k_h</td>
<td>Dimensionless</td>
<td>0.02 – 0.20</td>
<td>Vertical to horizontal permeability ratio</td>
</tr>
<tr>
<td>GF</td>
<td>Dimensionless</td>
<td>0.01 – 1.00</td>
<td>Geometric factor for Well-1 in layer-3</td>
</tr>
</tbody>
</table>

Following this protocol, one hundred data sets were generated. All hundred cases were automatically fed to the black oil reservoir simulator. The output data were the production profiles of Wells 1 and 2, namely oil production rate, water production rate, and block pressure for the hundred cases covering the period from 2000 to 2007. This period is composed of 38 time steps. Therefore, we have a total of 228 output parameters for the six production profiles.

5.1.1 Forward Solution

The artificial neural network receives the five uncertain parameters as input and then outputs the production rates and pressures for the two wells. First, the input and output data were normalized between -1 and 1. The input data was converted into logarithmic scale to reduce the gap among the parameter ranges. The hundred data sets were then randomly divided into 70 training sets, 18 validation sets, and 12 testing sets. Finding the best training algorithm involves a trial and error procedure. The best results were obtained using a neural network with one hidden layer consisting of 49 neurons. The training function used was the scaled conjugate gradient (trainscg), and the transfer function is the log sigmoid transfer function (logsig). The gradient descent with momentum weight and bias learning function (learnngdm) was used as the adaptation
learning function. The performance function was evaluated using the mean squared error with regularization performance function (msereg). MATLAB® was used to run the artificial neural network algorithm. Figure 5.2 shows a schematic of the artificial neural network developed for the reservoir under consideration.

The neural network was trained with a goal to minimize the error in the testing data subset. In this case, the average percentage error in the testing set was 6.3%. Figure 5.3 shows how close the results obtained from the neural network are against one of the cases from the testing set. All other test cases show similar behavior.

Figure 5.2: Schematic structure of the forward solution artificial neural network
5.1.2 Backward Solution

The backward solution is generally used to estimate the causes from the observed results (Ogawa & Nakamura, 2011). In this case, applying the inverse solution will solve for the five unknown reservoir properties given the production profiles of the two wells. Again, finding the best neural network training parameters involves trial and error. In this case, a neural network containing one hidden layer with 220 neurons provided the optimum results. The same training parameters of the forward solution were used. The number of training, validation and testing sets were also the same.

The average error in the testing data set was 3%. When the production profiles from the base reservoir model were fed to the inverse solution neural network, the results were very close. Table-5.2 summarizes the performance of the backward solution model when applied to the original base case model.
Table-5.2: Results of the backward solution of the neural network

<table>
<thead>
<tr>
<th>Prop</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>OOWC</td>
<td>3.207</td>
<td>5.540</td>
<td>1.383</td>
<td>8.846</td>
<td>4.818</td>
<td>1.503</td>
<td>2.663</td>
<td>1.916</td>
<td>0.419</td>
<td>0.043</td>
<td>3.269</td>
<td>0.814</td>
</tr>
<tr>
<td>φ</td>
<td>0.010</td>
<td>0.015</td>
<td>0.001</td>
<td>0.003</td>
<td>0.008</td>
<td>0.012</td>
<td>0.008</td>
<td>0.007</td>
<td>0.002</td>
<td>0.005</td>
<td>0.003</td>
<td>0.011</td>
</tr>
<tr>
<td>kv/kh</td>
<td>0.003</td>
<td>0.001</td>
<td>0.001</td>
<td>0.013</td>
<td>0.007</td>
<td>0.001</td>
<td>0.006</td>
<td>0.007</td>
<td>0.007</td>
<td>0.000</td>
<td>0.008</td>
<td>0.004</td>
</tr>
<tr>
<td>GF</td>
<td>0.007</td>
<td>0.032</td>
<td>0.048</td>
<td>0.014</td>
<td>0.061</td>
<td>0.002</td>
<td>0.042</td>
<td>0.016</td>
<td>0.001</td>
<td>0.021</td>
<td>0.021</td>
<td>0.012</td>
</tr>
</tbody>
</table>

Validating the results with the reservoir simulator is part of the workflow. In this case, the error is very marginal, which eliminates the need of the validation. Tables 5.3-a and 5.3-b show the error matrix for the 12 test cases in absolute error and percentage error, respectively.

Table 5.3-a: Absolute errors of the test cases

<table>
<thead>
<tr>
<th>Property</th>
<th>Original Value</th>
<th>ANN Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>OOWC</td>
<td>5150</td>
<td>5148</td>
</tr>
<tr>
<td>φ</td>
<td>0.23</td>
<td>0.233</td>
</tr>
<tr>
<td>k</td>
<td>100</td>
<td>96.6</td>
</tr>
<tr>
<td>kv/kh</td>
<td>0.1</td>
<td>0.103</td>
</tr>
<tr>
<td>GF</td>
<td>1.0</td>
<td>1.01</td>
</tr>
</tbody>
</table>

Table 5.3-b: Percentage errors of the test cases

<table>
<thead>
<tr>
<th>Prop</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>OOWC</td>
<td>0.063</td>
<td>0.108</td>
<td>0.027</td>
<td>0.171</td>
<td>0.093</td>
<td>0.029</td>
<td>0.052</td>
<td>0.037</td>
<td>0.008</td>
<td>0.001</td>
<td>0.064</td>
<td>0.016</td>
</tr>
<tr>
<td>φ</td>
<td>4.358</td>
<td>5.972</td>
<td>0.547</td>
<td>1.217</td>
<td>3.257</td>
<td>4.347</td>
<td>2.988</td>
<td>2.580</td>
<td>0.859</td>
<td>2.215</td>
<td>1.077</td>
<td>3.690</td>
</tr>
<tr>
<td>k</td>
<td>4.292</td>
<td>3.067</td>
<td>2.721</td>
<td>0.736</td>
<td>2.118</td>
<td>6.726</td>
<td>1.485</td>
<td>2.280</td>
<td>5.058</td>
<td>2.773</td>
<td>3.134</td>
<td>3.792</td>
</tr>
<tr>
<td>kv/kh</td>
<td>2.243</td>
<td>6.483</td>
<td>0.609</td>
<td>13.103</td>
<td>4.585</td>
<td>1.160</td>
<td>5.605</td>
<td>4.201</td>
<td>6.664</td>
<td>0.180</td>
<td>6.595</td>
<td>3.168</td>
</tr>
</tbody>
</table>
5.2 11 Uncertain Parameters

The previous workflow is applied to this case, but here there are 11 uncertain parameters instead of 5. The same reservoir in the previous case is used. In addition to the five parameters in the previous example, the skin of Well-1 is added to the uncertain parameters as well as the aquifer parameters. Aquifer parameters include the aquifer thickness, porosity, permeability, radius, and angle of exposition. Table 5.4 shows the range of uncertainty of the 11 parameters.

Following this protocol, one hundred data sets were generated. All hundred cases were automatically fed to the black oil reservoir simulator. The output data were the production profiles of Wells 1 and 2, namely oil production rate, water production rate, and block pressure for the hundred cases covering the period from 2000 to 2007. This period is composed of 39 time steps. Therefore, there are 234 output parameters for the six production profiles.

Table 5.4: Ranges of uncertain parameters

<table>
<thead>
<tr>
<th>Property</th>
<th>Unit</th>
<th>Value</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>OOWC</td>
<td>ft</td>
<td>5100 – 5180</td>
<td>Original oil-water contact</td>
</tr>
<tr>
<td>φ</td>
<td>Dimensionless</td>
<td>0.2 – 0.3</td>
<td>Porosity</td>
</tr>
<tr>
<td>k</td>
<td>md</td>
<td>50 – 150</td>
<td>Horizontal permeability</td>
</tr>
<tr>
<td>kv/kh</td>
<td>Dimensionless</td>
<td>0.02 – 0.2</td>
<td>Vertical to horizontal permeability ratio</td>
</tr>
<tr>
<td>GF</td>
<td>Dimensionless</td>
<td>0.01 – 1.0</td>
<td>Geometric factor for Well-1 in layer-3</td>
</tr>
<tr>
<td>Skin</td>
<td>Dimensionless</td>
<td>0 – 5</td>
<td>Skin factor of Well-1</td>
</tr>
<tr>
<td>h_a</td>
<td>ft</td>
<td>50 – 200</td>
<td>Aquifer thickness</td>
</tr>
<tr>
<td>φ_a</td>
<td>Dimensionless</td>
<td>0.10 – 0.37</td>
<td>Aquifer porosity</td>
</tr>
<tr>
<td>k_a</td>
<td>md</td>
<td>50 – 300</td>
<td>Aquifer permeability</td>
</tr>
<tr>
<td>r_a</td>
<td>ft</td>
<td>5000 – 20000</td>
<td>Aquifer radius</td>
</tr>
<tr>
<td>θ_a</td>
<td>Degree</td>
<td>0.5 – 1.0</td>
<td>Aquifer angle of exposition</td>
</tr>
</tbody>
</table>
5.2.1 Forward Solution

The artificial neural network receives the 11 uncertain parameters as input and then outputs the production rates and pressures for the two wells. Three functional links are used in the input to facilitate training convergence. These are \((k/\phi)^{0.5}\) for reservoir, \((k/\phi)^{0.5}\) for aquifer, and OOWC/aquifer radius. This brings the total input parameters to 14. The hundred data sets were then randomly divided into 70 training sets, 18 validation sets, and 12 testing sets. Finding the best training algorithm involves a trial and error procedure. The best results were obtained using a neural network with one hidden layer consisting of 183 neurons. The training function used was the scaled conjugate gradient (trainscg), and the transfer function is the log sigmoid transfer function (logsig). The gradient descent with momentum weight and bias learning function (learngdm) was used as the adaptation learning function. The performance function was evaluated using the mean squared error with regularization performance function (msereg). MATLAB® was used to run the artificial neural network algorithm.

The neural network was trained with a goal to minimize the error in the testing data subset. In this case, the average relative percentage error is used to report the error. This is to subdue the errors reported for small numbers such as the water rate at the initial production. The error is reported for the oil rate, water rate, and pressure. The maximum relative error is reported. The average relative error in the testing set was 3.5. Figure 5.4 shows how close the results obtained from the neural network are against one of the cases from the testing set. All other test cases show similar behavior.
5.2.2 Backward Solution

Applying the backward solution will solve for the 11 unknown reservoir properties given the production profiles of the two wells. Again, finding the best neural network training parameters involves trial and error. In this case, a neural network containing one hidden layer with 32 neurons provided the optimum results. The same training parameters of the forward solution were used. The number of training, validation and testing sets were also the same.

The average relative error in the testing data set was 12.9. When the production profiles from the base reservoir model were fed to the inverse solution neural network, the results were very close. Table-5.5 summarizes the performance of the backward solution model when applied to the original base case model.

Validating the results with the reservoir simulator is part of the workflow. After feeding the results from the neural network back to the reservoir simulator, the results are within acceptable range. Table 5.6 shows the absolute error matrix for the 12 test cases. Figures 5.5-a and 5.5-b show a comparison between the reservoir simulator result and the neural network result of the performance of Well-1 and Well-2.
Figure 5.4: Results of the forward solution of the neural network

Table 5.5: Results of the backward solution of the neural network

<table>
<thead>
<tr>
<th>Property</th>
<th>Original Value</th>
<th>ANN Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>OOWC</td>
<td>5150</td>
<td>5150.7</td>
</tr>
<tr>
<td>$\phi$</td>
<td>0.23</td>
<td>0.23</td>
</tr>
<tr>
<td>$k$</td>
<td>100</td>
<td>105</td>
</tr>
<tr>
<td>$kv/kh$</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>GF</td>
<td>1.0</td>
<td>0.87</td>
</tr>
<tr>
<td>Skin</td>
<td>1.0</td>
<td>0.46</td>
</tr>
<tr>
<td>$h_a$</td>
<td>100</td>
<td>119</td>
</tr>
<tr>
<td>$\phi_a$</td>
<td>0.3</td>
<td>0.22</td>
</tr>
<tr>
<td>$k_a$</td>
<td>150</td>
<td>168</td>
</tr>
<tr>
<td>$r_a$</td>
<td>10000</td>
<td>15581</td>
</tr>
<tr>
<td>$\theta_a$</td>
<td>0.75</td>
<td>0.69</td>
</tr>
</tbody>
</table>
Table 5.6: Absolute errors of the test cases of the backward neural network

<table>
<thead>
<tr>
<th>Prop</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>OWC</td>
<td>10.2</td>
<td>0.5</td>
<td>5.5</td>
<td>9.8</td>
<td>5.0</td>
<td>0.2</td>
<td>2.3</td>
<td>1.2</td>
<td>9.8</td>
<td>10.9</td>
<td>13.1</td>
<td>4.2</td>
</tr>
<tr>
<td>( \phi )</td>
<td>0.004</td>
<td>0.023</td>
<td>0.002</td>
<td>0.007</td>
<td>0.006</td>
<td>0.005</td>
<td>0.004</td>
<td>0.012</td>
<td>0.030</td>
<td>0.020</td>
<td>0.010</td>
<td>0.001</td>
</tr>
<tr>
<td>( k )</td>
<td>9.93</td>
<td>12.61</td>
<td>0.78</td>
<td>20.79</td>
<td>4.18</td>
<td>11.71</td>
<td>9.94</td>
<td>36.60</td>
<td>4.45</td>
<td>4.43</td>
<td>18.54</td>
<td>1.71</td>
</tr>
<tr>
<td>( kv/kh )</td>
<td>0.00</td>
<td>0.03</td>
<td>0.01</td>
<td>0.00</td>
<td>0.01</td>
<td>0.00</td>
<td>0.01</td>
<td>0.02</td>
<td>0.03</td>
<td>0.01</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>GF</td>
<td>0.10</td>
<td>0.06</td>
<td>0.04</td>
<td>0.16</td>
<td>0.11</td>
<td>0.16</td>
<td>0.27</td>
<td>0.02</td>
<td>0.13</td>
<td>0.03</td>
<td>0.07</td>
<td>0.10</td>
</tr>
<tr>
<td>Skin</td>
<td>0.5</td>
<td>0.1</td>
<td>0.2</td>
<td>0.5</td>
<td>0.8</td>
<td>0.4</td>
<td>0.3</td>
<td>1.3</td>
<td>0.0</td>
<td>0.3</td>
<td>0.5</td>
<td>0.3</td>
</tr>
<tr>
<td>( h_a )</td>
<td>27.7</td>
<td>39.5</td>
<td>4.9</td>
<td>17.8</td>
<td>44.1</td>
<td>48.7</td>
<td>41.0</td>
<td>18.2</td>
<td>1.5</td>
<td>13.4</td>
<td>37.8</td>
<td>29.1</td>
</tr>
<tr>
<td>( \phi_a )</td>
<td>0.054</td>
<td>0.003</td>
<td>0.060</td>
<td>0.082</td>
<td>0.065</td>
<td>0.048</td>
<td>0.111</td>
<td>0.116</td>
<td>0.026</td>
<td>0.117</td>
<td>0.004</td>
<td>0.030</td>
</tr>
<tr>
<td>( k_a )</td>
<td>47.55</td>
<td>76.42</td>
<td>16.93</td>
<td>47.90</td>
<td>44.32</td>
<td>21.37</td>
<td>73.76</td>
<td>99.06</td>
<td>104.26</td>
<td>160.92</td>
<td>61.67</td>
<td>49.80</td>
</tr>
<tr>
<td>( r_a )</td>
<td>622</td>
<td>2683</td>
<td>7737</td>
<td>1661</td>
<td>1933</td>
<td>816</td>
<td>3620</td>
<td>980</td>
<td>2869</td>
<td>3567</td>
<td>5082</td>
<td>3018</td>
</tr>
<tr>
<td>( \theta_a )</td>
<td>0.1</td>
<td>0.2</td>
<td>0.2</td>
<td>0.1</td>
<td>0.2</td>
<td>0.0</td>
<td>0.0</td>
<td>0.2</td>
<td>0.1</td>
<td>0.1</td>
<td>0.2</td>
<td>0.2</td>
</tr>
</tbody>
</table>

Figure 5.5-a: Well-1 Performance
5.3 Dealing with Highly Complex Scenarios

The previous concept was further enhanced to accommodate more complex cases. The modification arose from the reality that artificial neural network cannot obtain good results from the first pass in a complex reservoir in the presence of other uncertainties. The available historical data is used to feed the inverse solution neural network to obtain a starting point for the history matching parameters. As the production continues, the additional data is used to further enhance the neural network training. Then, the outcome is used as a guide to reducing the uncertainty in the reservoir parameters. The parameter values of the history matching are compared to those predicted by the neural network. If the values are close, the uncertainty of the parameters is reduced to around the values of the history match and the neural network, subject to the engineer’s discretion. If the
values do not match, the original uncertainty is maintained. History matching is performed again to accommodate the new changes.

To illustrate this approach, a more complex reservoir is considered. The reservoir is a rectangular (29x29x8) block model and is divided into seven regions, each of which has its own porosity and permeability, but all regions share three sets of relative permeability curves. There is a weak aquifer below the reservoir and the OWC is at the top of Layer 7. The reservoir is on production via three vertical wells, which are supported by two injectors. There are 38 uncertain parameters in this reservoir. These are the original oil water contact (OWC), porosity and horizontal permeability for each region, vertical-lateral permeability ratio ($k_v/k_h$), rock compressibility, net to gross ratio, relative permeability curves (end point saturations, $k_r$ at end point saturations, and Corey’s exponents), Aquifer properties (porosity, permeability, thickness, radius, and angle of exposition of the aquifer). Each of these parameters has a range of uncertainty. Figure-5.6 is a top view of the reservoir’s permeability distribution.

![Figure 5.6: Top view of the reservoir permeability distribution](image)

Figure 5.6: Top view of the reservoir permeability distribution
5.3.1 History Matching

A quick history matching process was applied to this reservoir. Table 5.7 compares the 38 uncertain parameters obtained from the history match with the actual reservoir data. Figures 5.7 a through e show plots of the history matching performance of the two producers and two injectors. As it can be seen, the results are decent. However, there is some room to improve. Table 5.8 shows the 38 uncertain parameters with their uncertainty ranges. The scattered points refer to the observed data while the solid/dashed lines refer to simulated data.

Table 5.7: history Matching results

<table>
<thead>
<tr>
<th>Property</th>
<th>OWC</th>
<th>netgross</th>
<th>kv</th>
<th>compres</th>
<th>A_h</th>
<th>A_por</th>
<th>A_k</th>
<th>A_r</th>
<th>A_ang</th>
<th>Swcon1</th>
<th>Sorw1</th>
<th>Krwiro1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual</td>
<td>5150</td>
<td>0.8</td>
<td>0.1</td>
<td>4.5</td>
<td>100</td>
<td>0.25</td>
<td>100</td>
<td>2000</td>
<td>0.75</td>
<td>0.16</td>
<td>0.2</td>
<td>0.4</td>
</tr>
<tr>
<td>Original HM</td>
<td>5152</td>
<td>0.8</td>
<td>0.1</td>
<td>5.5</td>
<td>102</td>
<td>0.31</td>
<td>94</td>
<td>1520</td>
<td>1</td>
<td>0.17</td>
<td>0.31</td>
<td>0.42</td>
</tr>
<tr>
<td>Krocw1</td>
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Figure 5.7-a: History Matching Performance of Well-1

Figure 5.7-b: History Matching Performance of Well-3
Figure 5.7-c: History Matching Performance of Well-4

Figure 5.7-d: History Matching Performance of Well-2
Figure 5.7-e: History Matching Performance of Well-5
### Table 5.8: Ranges of uncertain parameters

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<td>Aq. Thickness</td>
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<tr>
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</tr>
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<tr>
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<td>Porosity 4</td>
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<td>Permeability 2</td>
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<td>Permeability 7</td>
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#### 5.3.2 Forward Solution

A total of 400 cases were generated through CMOST to be used for the neural network training. The data was divided into 280 training data sets, 72 validation data sets, and 48 testing data sets. There are 38 input parameters and 507 output parameters. The output parameters consist of the oil production rates of 3 wells, water production rates for 3 wells, block pressures for 5 wells, and bottom hole pressures for 2 injectors, all span for 39 time steps from year 2000 to 2007. The training parameters were the same as the
previous case. The criterion for choosing the optimum outcome is based on two factors. The first is the correlation coefficient between the observed and calculated data. The second is the normalized root mean square error (NRMSE) between the observed and calculated data as follows:

\[
\varepsilon = \sqrt{\frac{\sum (\text{ANN} - \text{Observed})^2}{n \cdot \text{Max(Observed)} - \text{Min(Observed)}}} \tag{5.1}
\]

where \( n \) is the number of data points. The complexity of the problem was quite high such that the artificial neural network could not get a decent match for the forward solution. Figure 5.8 is an example of the mismatch between the observed and calculated data.

Figure 5.8: The mismatch in the ANN prediction
### 5.3.3 Backward Solution and Iterative Update

The failure to get a good match prompted the idea of using new production data in the training was brought in to the analysis. The inverse neural network was then constructed. This time, the inputs were the production rates, pressures, and injection bottom hole pressure, while the outputs were the 38 reservoir properties. The training only covered the history period from 2000 to 2007. The average percentage error was still high at 14%, NRMSE was 0.286, and the correlation coefficient was 0.9984. A quick assisted history matching should be attempted first because its output parameters would be compared to those generated from the neural network. Table 5.9 shows the results obtained by both the history matching and the neural network. The values in red indicate a noticeable difference between history matching and neural network.

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Whenever the parameter value from the history match and the neural network is within a pre-defined range of agreement from each other, the range of uncertainty is reduced for that particular parameter, otherwise it is maintained the same. The new range of parameters is then fed back to the assisted history matching software to improve the results. With each additional production period, the neural network is re-trained and results are compared to the latest history matching parameters. The process is repeated as long as there is an improvement in the match. Figure 5.9 shows the improvement of the history matching parameters after two iterations.

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Figure 5.9: Improvement of the history match parameters
This method can be implemented to an already history-matched model to try to improve the matching parameters, or it can be applied to create a starting point for a newly created reservoir simulation model. Figure 5.10 illustrates the general workflow of this approach.

Figure 5.10: Workflow diagram of the approach to reduce uncertainty

The workflow may be applied as long as new data become available and the engineer believes that there is more room to improve the history match. This approach will also try to fine-tune the reservoir parameters and bring them closer to the actual values. Figures 5.11 a through e shows the history match of the five wells after three iterations of the history matching update protocol, i.e., up to start of 2010.
Figure 5.11-a: History matching performance of Well-1

Figure 5.11-b: History matching performance of Well-3
Figure 5.11-c: History matching performance of Well-4

Figure 5.11-d: History matching performance of Well-2
One of the shortcomings of some previous studies is that they did not address whether the results from the assisted history match using expert systems still produce good predictions. Since the history matching solution is non-unique, the reservoir properties need to be updated regularly to keep the match in good shape. Hence this approach is applied to bring the reservoir properties closer to their actual values, which will yield better prediction capabilities for the reservoir simulator. Figures 5.12 a through j compare the prediction models from the original history match and the refined results using the expert system. The scattered points refer to the observed data while the solid/dashed lines refer to simulated data. It can be noticed that the data coming from the expert system is able to enhance the prediction quality.
Figure 5.12-a: Standard prediction performance of Well-1

Figure 5.12-b: Expert system assisted prediction performance of Well-1
Figure 5.12-c: Standard prediction performance of Well-3

Figure 5.12-d: Expert system assisted prediction performance of Well-3
Figure 5.12-e: Standard prediction performance of Well-4

Figure 5.12-f: Expert system assisted prediction performance of Well-4
Figure 5.12-g: Standard prediction performance of Well-2

Figure 5.12-h: Expert system assisted prediction performance of Well-2
Figure 5.12-i: Standard prediction performance of Well-5

Figure 5.12-j: Expert system assisted prediction performance of Well-5
Chapter 6 Development of Diagnostic Expert Systems:

Formation Damage

Once a satisfactory history match is achieved, the reservoir simulation model is used to predict the reservoir performance. This chapter and the next three describe the process of developing four expert systems that can identify the causes of unexpected reservoir behavior. The definition of unexpected behavior refers to the drastic deviation of the observed field data from the reservoir simulation prediction. The base reservoir model is well history-matched and performs good prediction. Therefore, any major deviation of the observed data should raise a flag. This chapter and subsequent chapters will cover the topics of formation damage in terms of plugged perforation and skin, hydraulic fracturing, reservoir compaction, and tarmat breakdown.

This chapter describes the unexpected production behavior resulting from formation damage. Formation damage refers to the reduction of the effective permeability near the wellbore. There are several causes of formation damage including but not limited to the completion and workover fluid, fines movement, and scale deposition. In the following sections, the effect of plugged perforation sets and skin are examined.

6.1 Plugged Perforation

An expert system of artificial neural networks is used to detect whether the production rate decline or abnormal pressure behavior is caused by plugged perforations. The same heterogeneous reservoir in section 5.3 is used in this part of the study. However, here only Well-1 will be focused on. Well-1 has three sets of perforations, one set in each layer. The reservoir engineer believes the bottom perforation is susceptible to
decreasing productivity index (PI) within one year of production. Figure 5.6 is a top view of the reservoir permeability distribution. The study covers the period from 2000 to 2007.

6.1.1 Forward Solution

To construct the forward solution, the neural network has 8 input parameters. These are 8 random PI multipliers, one for each year. The PI of the perforation set can decrease by up to 40% each year. A PI factor of 1 means the perforations are fully open and a value of 0 means the perforations are completely plugged. For simplicity, the changes are assumed to happen at one day, instead of going gradual. The output parameters are Well-1 oil rate, water rate, and block pressure from 2000 to 2007. The reservoir model is used to generate and run 200 data sets, of which 150 is used for training, 30 for validating, 20 for testing. The same parameters for the network training are used as in the previous section. A network of 1 hidden layer and 25 neurons gave the least error. The error in the testing data set is very minimal. Figure 6.1 shows the neural network prediction of one of the testing data sets after it was fed with the PI factors. The remaining testing samples show excellent match as well.

6.1.2 Backward Solution

The backward solution is used to predict the changes in the PI factor for the third set of perforations. This change is expected to be annual. The backward solution is performed after each unexpected noticeable change in the rates or pressure. Figure 6.2 shows the production profile after 18 months of production. There is some deviation from the expected rates and pressure, although not drastic. A neural network with two hidden layers with 49 and 25 neurons, respectively, was used for the training. The same data set
from the forward solution is used for training, but the data is limited to 18 months. That means the inputs are the oil rate, water rate, and pressure for the first 18 months, and the output is the first PI factor. The actual PI factor is 0.8, which is what the network predicted. The actual PI factor became 0.8 after 300 days. The network is trained to predict the PI factor at 300 days. So, what happens if actual change happens at a different date? An example where the actual plugging (PI factor = 0.8) was delayed by 3 months (day 390) was fed to the network. The neural network predicted the PI factor to be 0.83 at day 300.

The PI factor value of 0.8 at 300 days is fed back to the model so that a good match can be re-established. After another year of production, the changes were minimal and thus the engineer decides to keep the model unchanged. The actual PI factor after year 2 is 0.69. Figure 6.3 shows the production profile after 30 months of production.
Figure 6.2: Production profile after 18 months of production

Figure 6.3: Production profile after 30 months of production
After 3 years of production, some changes in the rates and pressure are noticed. Figure 6.4 shows the production profile after 42 months of production. The neural network was run to determine if the perforation set productivity factor was reduced again. The inputs to the network are the oil rate, water rate, and pressure up 42 months since production started. The outputs of the network are three PI factors, one for each year. The actual value of the PI factor for the third year is 0.5. This network used the same structure used for the last network. The network outputs for the three PI factors are 0.80, 0.68, and 0.51. These results are almost identical to the actual values of 0.80, 0.69, and 0.50. The process can then continue as long as a noticeable change is observed.

![Figure 6.4: Production profile after 42 months of production](image-url)
6.1.3 Changes after the Default Times

The neural network is trained to report PI factor values at pre-defined dates. Now, the actual changes will occur at different dates than what is the network is trained to report. The previous example is used again after three years of production, which means three different values for the PI factors. The actual dates of the PI factor changes are 300, 481, and 1111 days since the start of the production. By default, the network will predict the PI factors at 300, 661, and 1021 days. For this example, the network predicted PI factor values of 0.764, 0.719, and 0.465, respectively. Figure 6.5 is a schematic diagram of the timeline of PI factor changes. To put the output of the neural network into perspective, the values are fed to the reservoir simulation and the results are compared to the actual production profile. Figure 6.6 shows this comparison.

Figure 6.5: Timeline of PI factor changes
In this section, an expert model is developed to detect if the overall skin factor of the well causes an unexpected production behavior. For the same reservoir, Well-1 has zero skin at the start of production. Based on previous studies, the reservoir engineer believes the well is developing positive skin within a year of production. The skin is modeled by randomly increasing the skin values by as much as 1.5 units each year.

### 6.2.1 Forward Solution

To construct the forward solution, the neural network has 8 input parameters. These are 8 skin values, one for each year. The skin factor can increase by up to 1.5 units each year. For simplicity, the changes are assumed to happen at one day, instead of going gradual. The output parameters are Well-1 oil rate, water rate, and block pressure from
2000 to 2007. The reservoir model is used to generate and run 200 data sets, of which 150 is used for training, 30 for validating, 20 for testing. The same parameters for the network training are used as in the previous section. A network of 1 hidden layer and 27 neurons gave the least error. The error in the testing data set is very minimal. Figure 6.7 shows the neural network prediction of one of the testing data sets after it was fed with the skin factors. The remaining testing samples show excellent match as well.

![Graph showing ANN forward solution prediction]

Figure 6.7: ANN forward solution prediction

6.2.2 Backward Solution

The backward solution is used to predict the changes in the skin factor for the third set of perforations. This change is expected to be annual. The backward solution is performed after each unexpected noticeable change in the rates or pressure. Figure 6.8 shows the production profile after 18 months of production. There is some deviation from
the expected rates and pressure, although not drastic. A neural network with two hidden layers with 44 and 22 neurons, respectively, was used for the training. The same data set from the forward solution is used for training, but the data is limited to 18 months. That means the inputs are the oil rate, water rate, and pressure for the first 18 months, and the output is the first skin factor.

![Flow profile after 18 months of production](image)

Figure 6.8: Flow profile after 18 months of production

The actual skin factor is 1.0, which is what the network predicted. The actual skin factor became 0.8 after 300 days. The network is trained to predict the skin factor at 300 days. So, what happens if actual change happens at a different date? An example where the actual skin factor change (skin = 1.0) was delayed by 3 months (day 390) was fed to the network. The neural network predicted the skin factor to be 0.71 at day 300.
The skin factor value of 1.0 at 300 days is fed back to the model so that a good match can be re-established. After another year of production, some changes in the rates and pressure are noticed. Figure 6.9 shows the production profile after 30 months of production. The neural network was run to determine if the skin factor increased again. The inputs to the network are the oil rate, water rate, and pressure up 30 months since production started. The outputs of the network are two skin factors, one for each year. The actual value of the skin factor for the second year is 1.75. This network used the same structure used for the last network. The network outputs for the two skin factors are 1.01 and 1.77. These results are almost identical to the actual values of 1.0 and 1.75.

Figure 6.9: Production profile after 30 months
The skin factor value of 1.75 at year 2 is fed back to the model so that a good match can be re-established. After another year of production, the changes were minimal and thus the engineer decides to keep the model unchanged. The actual PI factor after year 3 is 1.9. Figure 6.10 shows the production profile after 42 months of production.

![Production profile after 42 months of production](image)

Figure 6.10: Production profile after 42 months of production

After four years of production, some changes in the rates and pressure are again noticed. Figure 6.11 shows the production profile after 30 months of production. The neural network was run to determine if the skin factor increased again. The inputs to the network are the oil rate, water rate, and pressure up 54 months since production started. The outputs of the network are two skin factors, for the last two years. The actual value of the skin factor for the fourth year is 2.6. This network used the same structure used for
the last network. The network outputs for the two skin factors are 1.91 and 2.62. These results are almost identical to the actual values of 1.9 and 2.6. The process can then continue as long as a noticeable change is observed.

Figure 6.11: Production profile after 54 months

6.3 Mixed Expert Systems of Plugged Perforation and Skin

This expert system is developed to detect if the unexpected changes occurred because of the overall skin factor, a plugged set of perforations, or both. To illustrate this concept, the expert system will analyze the production profile in figure 6.12 to determine the cause of the changes. This is still the same reservoir and only Well-1 is affected. The well has been producing for 30 months.
Figure 6:12: Production profile after 30 months of production

This production profile is fed to the individual expert systems. Each system is expected to return two values of PI factors or skin factors for two years of production after the first year, namely at days 330 and 661. The plugged perforation expert systems predicted PI factors of 0.997 and 0.548 for years 1 and 2, respectively. The skin expert system predicted skin values of 0.065 and 0.916 for years 1 and 2, respectively. These values are individually fed to the reservoir simulation model to first check if the change can be attributed to one of them only. Figure 6.13 compares the output from both expert systems with the actual profile. It can be detected that the plugged set of perforations has caused the change. The actual PI factors are 1 and 0.55.
Another example is the production profile in Figure 6.14. The well has been producing for 42 months and there are three changes in production behavior. This production profile is fed to the individual expert systems. Each system is expected to return three values of PI factors or skin factors for three years of production after the first year, namely at days 330, 661, and 1021. The plugged perforation expert systems predicted PI factors of 0.878, 0.679, and 0.452 for years 1, 2, and 3, respectively. The skin expert system predicted skin values of 0.10, 0.50, and 1.38 for years 1, 2 and 3, respectively. These values are individually fed to the reservoir simulation model to first check if the change can be attributed to one of them only. Figure 6.15 compares the output from both expert systems with the actual profile. It can be detected that the overall skin has caused the change. The actual skin factors are 0.1, 0.5 and 1.4.
Figure 6.14: Production profile after 42 months of productions

Figure 6.15: Comparison of the output of the two expert systems
In the previous two examples, there was no need for the mixed expert system that can predict the two factors acting together since only one factor was acting the whole time. To test this system, the production profile in Figure 6.16 is considered. The well has been producing for 30 months and there are two changes in the production profile. When the production profile is fed to the individual system, the perforation system returned values of 0.788 and 0.283 for years 1 and 2 respectively. The skin system returned values of 0.357 and 1.82, respectively. Figure 6.17 shows a comparison of the output of the two systems plotted individually. It can be logically assumed that the plugged perforation set is acting in year 1 while the skin is acting in year 2. Figure 6.18 is the production profile plot with PI factor of 0.788 for year one and skin factor of 1.82 for year 2.

![Figure 6.16: Production profile after 30 months of production](image)
Still, the production profile is not matched, which indicates that both factors are acting together. It is now the time to test the mixed expert system. This expert system utilizes neural networks to predict the PI and skin factors for each year of production. It is
trained similar to the previous two systems, except there are two outputs for each year, which are the PI factor and skin factor. Training the network with a wide range of combinations of these two factors allows it to predict the required values fairly accurately. For this example, the network’s input is the well’s oil rate, water rate, and pressure for 30 months while the outputs are the PI factors and skin factors for two years. The network is then provided with the production profiles and its outputs for the PI factors are 0.77 and 0.75. The outputs for skin are 0.05 and 1.52 for years 1 and 2, respectively. Figure 6.19 shows how good the match is when the output data is validated by the reservoir simulator. The actual reservoir parameters are 0.8 and 0.8 for the PI factors and 0 and 1.5 for the skin factors.

![Reservoir Performance Graph](image)

**Figure 6.19:** The output of the mixed expert system compared to the observed data

In the previous example, the PI factor is acting in the first year while the skin factor is acting in the second year. The last example illustrates a more complex scenario where both factors are acting at the same time. Figure 6.20 shows the production profile
of a well that has been producing for 42 months and there are 3 changes in the production profile. When this production profile is fed into the two separate systems, the perforations system predicted PI factors of 0.777, 0.408, and 0.238. The skin system predicted 0.20, 1.45, and 2.78 for years 1, 2, and 3, respectively. Figure 6.21 shows a comparison between the outputs of the two systems when acting separately.

![Figure 6.20: Production profile after 42 months of production](image)

One can be satisfied with the output of the skin system to achieve a decent match. If the same profile is fed to the mixed system, the results are 0.95, 0.79, and 0.59 for the perforation system and 0.18, 1.21, and 1.71 for the skin system. Figure 6.22 shows the performance of the mixed system. The actual model values are 0.95, 0.8, and 0.6 for the PI factors and 0.2, 1.1, 1.75 for the skin factors.
Figure 6.21: Comparison of the output of the two expert systems

Figure 6.22: The output of the mixed expert system compared to the observed data

For these cases, the mixed expert system has proven that it can handle complex scenarios where more than one factor are contributing to the production change. The most critical factor in the success of this system is the engineer’s understanding of the reservoir dynamics and the various factors affecting its performance.
Chapter 7 Hydraulic Fracturing

Hydraulic fracturing is the fracturing of rock by a pressurized liquid. Hydraulic fracturing is usually applied to low permeability reservoir in order to enhance hydrocarbon production. The production is enhanced by converting the hydrocarbon flow into the wellbore from radial to near linear. Hydraulic fractures extend beyond the damaged zone near the wellbore and target better areas far from the wellbore. The most important parameters to characterize a hydraulic fracture are its half-length, width, and permeability. These parameters are incorporated into the reservoir simulation model in order to match the production profile after the fracture job is completed. In this section, an expert system is developed to check whether the hydraulic fractures have the same characteristics as they are believed to be. If the reservoir model is well history-matched, the prediction after the fracture job should not drastically deviate from the simulated data. If that happens, the expert system is introduced to help in figuring out the real characteristics of the hydraulic fractures.

7.1 The Reservoir Model

The reservoir model is a 15x15x8 block square model. The dimensions of each grid block are 200’x200’x25’. This is a tight reservoir with lateral permeability of 5 md and vertical permeability of 1 md for the homogeneous cases and permeability values of 1 to 10 md for the heterogeneous cases. The initial pressure of the reservoir is 4000 psi and the top of it is at 5000’. The oil-water contact is at the top of layer 7 at 5150’. There is a water aquifer at the bottom of the reservoir, which is modeled with Carter-Tracy method. There is one horizontal well completed in 5 blocks in the center of the reservoir.
in the x-direction in layer 2. This well produces at a constant bottom-hole pressure of 1500 psi. This is the only well in the reservoir. The study covers the period from 2000 to 2020. In the reservoir simulator, the fracture width cannot be less than the wellbore radius; therefore, it is usually modeled as 1 ft and then other fracture parameters are properly adjusted to arrive at a dimensionless fracture conductivity of the desired value. For example, if the actual fracture width is 0.001’ and the fracture permeability is 50,000 md, the effective permeability becomes $0.001' \times 50000 \text{ md} / 1' = 50 \text{ md}$. Hence the term effective fracture permeability will be used, which incorporates both the fracture width and permeability.

Since the reservoir is tight and doesn’t receive adequate pressure support, it was decided to fracture the well. The well is hydraulically fractured at the start of 2004. Figure 7.1 shows a representation of the well fracture structure within the reservoir model. Hydraulic fractures help increase the well production. Figures 7.2-a and b show how hydraulic fracturing increases the well productivity.

Figure 7.1: The structure of a hydraulically fractured well
In the next sections, four cases of hydraulic fracturing are discussed. The first one is for homogeneous reservoir and all fractures are the same. The second is for homogeneous reservoir and all fractures are different in terms of length, width, and
permeability. The third is for heterogeneous reservoir and all fractures are different. The last case is similar to the third, but fracture permeability is decreasing each year.

### 7.2 Homogeneous Reservoirs and Hydraulic Fractures

The reservoir is homogeneous with lateral permeability of 5 md and vertical permeability of 1 md. The well is fractured at the start of 2004. Three blocks out of five are fractured. All fractures have the same fracture half-length and effective permeability.

#### 7.2.1 Forward Solution

To construct the forward solution, 200 data sets are generated by the reservoir simulator, of which 150 are used for training, 30 for validating, and 20 for testing. The input parameters are the fracture half-length, which varies between 100’ and 300’, and the fracture effective permeability, which varies between 15 to 1415 md. The generated data has a fracture conductivity values ranges between 1 and 12. Fracture conductivity is defined in equation 2.22. According to Daneshy (2010), a reasonable range for the fracture density is between 1 and 10. Figure 7.3 shows a histogram of the fracture density distribution of the 200 data sets. The outputs of the neural network are the oil production rate, water production rate, well pressure, and cumulative oil rate. The output covers the period from 2004 to 2020 over 69 time steps, which brings the total number of output parameters to 276. The network was trained with the scaled conjugate gradient algorithm of 1 hidden layer with 22 neurons. The error was very marginal. Figure 7.4 shows two examples from the testing data set, where the neural network is able to predict the production profile based on the input of the fracture half-length and effective permeability.
Figure 7.3: Fracture conductivity distribution

Figure 7.4: ANN forward solution
7.2.2 Backward Solution

The neural network for the backward solution receives the production profile as an input and returns the fracture half-length and effective permeability as an output. Two backward neural networks are developed; one takes the production profile after one year of production after the fracture job and the other takes the production profile after two years of production. Figure 7.5 shows a cross-plot of the backward solution prediction of the half-length and effective permeability. The correlation coefficient between the predicted and actual parameters is very high. Figure 7.6 shows the same but after two years of production. The network prediction slightly improved after receiving more data.

Figure 7.5: ANN backward solution performance after 1 year of production
7.3 Homogeneous Reservoir, Varying Fracture Characteristics

This case is similar to the previous one but all five blocks are fractured and every fracture has a different half-length and effective permeability.

7.3.1 Forward Solution

For this network, 250 data sets are generated of which 187 are used for training, 33 for validating, and 25 for testing. The input to the network is the fracture half-length and effective permeability for each hydraulic fracture. A functional link of half-length/effective permeability is used to facilitate the network training, which brings the total of input parameters to 15. The same procedure is followed as in the previous case. The prediction error was very marginal. Figure 7.7 shows one example from the testing data set, where the neural network is able to predict the production profile based on the input of the fracture half-length and effective permeability for each of the five hydraulic fractures. The remaining testing sets show very accurate predictions as well.
7.3.2 Backward Solution

The neural network for the backward solution receives the production profile as an input and returns the fracture half-length and effective permeability for each hydraulic fracture as an output. Two backward neural networks are developed; one takes the production profile after one year of production after the fracture job and the other takes the production profile after two years of production. The first set of developed networks failed to predict the fracture characteristics with scaled conjugate gradient algorithm. The correlation coefficient between predicted and actual values of the fracture half-length and effective permeability were 0.45 and 0.76, respectively, after one year of production. The networks were then trained with the Bayesian regularization algorithm. This algorithm was able to produce more accurate results. The drawback of using this algorithm is that it requires a lot of memory and takes a lot of time to train. Figure 7.8 shows a cross-plot of the backward solution prediction of the half-length and effective permeability for all the fractures. The correlation coefficient between the predicted and actual parameters is
acceptable. Figure 7.9 shows the same but after two years of production. The network prediction greatly improved after receiving more data.

Figure 7.8: ANN backward solution performance after 1 year of production

Figure 7.9: ANN backward solution performance after 2 years of production

To validate the results with the reservoir simulation, one of the testing cases that hasn’t been introduced to the network during training is fed to the reservoir simulator and the network performance is plotted in Figure 7.10. The values of the fracture half-length and effective permeability for the actual and predicted cases are in Table-7.1.
Figure 7.10: Comparison between ANN predictions with the actual data

Table 7.1: Fracture half-length and effective permeability for the test case

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The network was perfectly able to match the oil production rate and the well pressure. However, it deviates slightly in the water production rate.
7.4 Heterogeneous Reservoir, Varying Fracture Characteristics

The next case is similar to the previous case, except the reservoir is heterogeneous. The reservoir has a random permeability distributed across all layers, which ranges between 1 and 10 md.

7.4.1 Forward Solution

For this network, 250 data sets are generated of which 187 are used for training, 33 for validating, and 25 for testing. The input to the network is the fracture half-length and effective permeability for each hydraulic fracture. A functional link of half-length/effective permeability is used to facilitate the network training, which brings the total of input parameters to 15. The same procedure is followed as in the previous case. The prediction error was very marginal. Figure 7.11 shows one example from the testing data set, where the neural network is able to predict the production profile based on the input of the fracture half-length and effective permeability for each of the five hydraulic fractures. The remaining testing sets show very accurate predictions as well.

Figure 7.11: ANN forward solution
7.4.2 Backward Solution

Again, two neural networks are developed to read data after one and two years of production. The network is trained with the Bayesian regularization algorithm. Figure 7.12 shows a cross-plot of the backward solution prediction of the half-length and effective permeability for all the fractures. The correlation coefficient between the predicted and actual parameters is acceptable. Figure 7.13 shows the same but after two years of production. The network prediction greatly improved after receiving more data.

Figure 7.12: ANN backward solution performance after 1 year of production

Figure 7.13: ANN backward solution performance after 2 years of production
7.5 Decreased Productivity Performance in the Fractures

This case is similar to the previous case in terms of heterogeneity and that each fracture has a different half-length and effective permeability. However, each of the five fractures is subject to losing up to 20% of its productivity each year after the first year due to fracture closure. This reduction will be modeled by assigning a random productivity index (PI) multiplier between 0 and 0.2 for each of the fractures. Then the new productivity index for the fracture will be PI*(1-random multiplier). This is a relative productivity index where a PI value of 1 indicates the fracture is fully open.

7.5.1 Forward Solution

For this network, 400 data sets are generated of which 300 are used for training, 60 for validating, and 40 for testing. The input to the network is the fracture half-length and effective permeability for each hydraulic fracture. In addition, there are 25 PI multipliers, one for each frac stage for the next 5 years. The same procedure is followed as in the previous case. The prediction error was very marginal. Figure 7.14 shows one example from the testing data set, where the neural network is able to predict the production profile based on the input of the fracture half-length, effective permeability and the PI multiplier for each of the five hydraulic fractures. The remaining testing sets show very accurate predictions as well.

7.5.2 Backward Solution

The network will read data after 2 and 3 years of production after the fracture job, which is 1 and 2 years after the productivity reduction. Figure 7.15 shows a cross-plot of network prediction of fracture length and effective permeability after 2 years of the
fracture job (1 year of PI reduction). Figure 7.16 shows a cross-plot of the PI values after the first years of production for each frac stage. Figure 7.17 shows a cross-plot of network prediction of fracture length and effective permeability after 3 years of the fracture job (2 years of PI reduction). Figure 7.18 shows a cross-plot of the PI values after the second years of production for each frac stage.

Figure 7.14: ANN forward solution

Figure 7.15: ANN backward solution performance after 2 years of production
Figure 7.16: PI values for each fracture after 2 years of production

Figure 7.17: ANN backward solution performance after 3 years of production

The network was able to fairly predict the fracture length and effective permeability although not as accurate as the previous examples. The extra year of production data only slightly improved the results, which is an indication that the problem is quite complex. To validate the results with the reservoir simulation, one of the testing cases that hasn’t been introduced to the network during training is fed to the reservoir simulator. Table 7.2 summarizes the results of the input. The network is trained
after receiving two years of data after the PI reduction started, which is three years after
the fracture job. Figure 7.19 shows how accurate the network is in predicting the fracture
characteristics. The plot shows reservoir performance until 2020.

![Fracture PI Cross Plot](image)

Figure 7.18: PI values for each fracture after 3 years of production

Table-7.2: Input data for the neural network

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<td>pi4_ y2</td>
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<td>0.731</td>
</tr>
<tr>
<td>kf5</td>
<td>565</td>
<td>673</td>
<td>pi5_ y2</td>
<td>0.688</td>
<td>0.689</td>
</tr>
</tbody>
</table>
In Table-7.2, HL refers to the fracture half-length and the number after it refers to the fracture stage. $k_f$ refers to the hydraulic fracture effective permeability. $p_{1-y1}$ refers to the new productivity index factor of the hydraulic fracture for stage one and after one year and so on.

Figure 7.19: Comparison between ANN predictions with the actual data
Chapter 8 Reservoir Compaction

Reservoir compaction is the process in which the compressive strength of the rock is exceeded and plastic deformation occurs. This results in irreversible reduction in porosity and permeability. The objective of this section is to develop an expert system that is able to identify the effect of porosity and permeability compaction on the reservoir production behavior.

8.1 Reservoir Model

The reservoir model is an 11x11x3 square block model with each block having dimensions of 100’x100’x500’. The top of the reservoir is at 8400’ and the initial pressure is 4800 psi. The porosity is constant at 0.3 while the permeability is constant across each layer at 200, 50, and 500, respectively. The last case has heterogeneous porosity and permeability. There is one vertical well completed at the center of the reservoir and penetrating the three layers. It is set to produce at a constant oil rate of 5000 STB/Day. The study covers the period from 2000 to 2015. Figure 8.1 shows a schematic diagram of the reservoir model.

Geomechanical data suggests that compaction causes a reduction of the bulk volume due to pore collapse. However, the reservoir simulator always assumes a constant bulk volume. To simulate the effect of reduced pore volume, the model increases the volume of the solid grain instead as in Figure 8.2. It is also assumed that these volumetric changes have little influence on saturation changes and multiphase flow behavior (Best, 2002).
Figure 8.1: Reservoir model used for the compaction study

Figure 8.2: Comparison between geomechanical and simulation model in terms of simulating compaction. Source: (Best, 2002)
The terms in Figure 6.42 are: $V_{bi} = \text{initial bulk volume}$, $V_{bf} = \text{compacted bulk volume}$, $V_{pi} = \text{initial pore volume}$, $V_{pf} = \text{compacted pore volume}$, $V_{gi} = \text{initial grain volume}$, and $V_{gf} = \text{compacted (enlarged) grain volume}$. Green represents the oil filled pore volume, blue is the initial water saturation, and orange circles are the grains.

### 8.2 Homogeneous Reservoir, One Rock Region

This model has a constant porosity of 0.3 and permeability values of 200, 50, and 500 md for layers 1, 2, and 3 respectively. The compaction is modeled as porosity and permeability multipliers. An example of typical porosity and permeability multipliers is tabulated in Table-8.1. Figure 8.3 is a plot of multipliers vs. pressure. In this model, the porosity multiplier increases by 0.02-0.05 every 1000 psi. The permeability multiplier increases by 0.05-0.18 every 1000 psi.

#### Table-8.1: An example of porosity and permeability variation with pressure

<table>
<thead>
<tr>
<th>P</th>
<th>Por mult</th>
<th>k mult</th>
</tr>
</thead>
<tbody>
<tr>
<td>14.7</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>100</td>
<td>1.0026</td>
<td>1.0069</td>
</tr>
<tr>
<td>200</td>
<td>1.0056</td>
<td>1.0151</td>
</tr>
<tr>
<td>500</td>
<td>1.0146</td>
<td>1.0401</td>
</tr>
<tr>
<td>1000</td>
<td>1.0296</td>
<td>1.0831</td>
</tr>
<tr>
<td>2000</td>
<td>1.0596</td>
<td>1.1745</td>
</tr>
<tr>
<td>3000</td>
<td>1.0896</td>
<td>1.2736</td>
</tr>
<tr>
<td>4000</td>
<td>1.1196</td>
<td>1.381</td>
</tr>
<tr>
<td>5000</td>
<td>1.1496</td>
<td>1.4975</td>
</tr>
<tr>
<td>6000</td>
<td>1.1796</td>
<td>1.6239</td>
</tr>
<tr>
<td>7000</td>
<td>1.2096</td>
<td>1.7609</td>
</tr>
<tr>
<td>8000</td>
<td>1.2396</td>
<td>1.9094</td>
</tr>
<tr>
<td>9000</td>
<td>1.2696</td>
<td>2.0705</td>
</tr>
<tr>
<td>10000</td>
<td>1.2996</td>
<td>2.2452</td>
</tr>
</tbody>
</table>
The effect of compaction on oil production could be significant. Compaction is considered one of the driving mechanisms that provide energy to the reservoir. Recoveries of this type of drives are greater than normal reservoirs. Figure 8.4 compares the oil production for a normal reservoir along with two other cases with compaction. The letter O denotes the original reservoir.

**Figure 8.3:** Porosity and permeability multipliers against pressure

**Figure 8.4:** Comparison of oil recovery between normal reservoir and compaction
8.2.1 Forward Solution

To develop the forward solution of this expert systems, 400 data sets, of which 300 are used for training, 60 for validating, and 40 for testing. The compaction table in the reservoir model starts at atmospheric pressure where the multiplier value is 1. After that, there are five pressure values at 1000, 2000, 3000, 4000, and 5000 psi. The value of multiplier at 1000 psi is $1 + \text{multiplier change}$. The inputs to the network are 5 porosity multipliers and 5 permeability multipliers for the values of pressures in the compaction table. The outputs are the oil production rate, gas production rate, well block pressure, and cumulative oil production. This covers the period from 2000 to 2015 over 66 time steps, which brings the total number of output parameters to 264. One hidden layer with 74 neurons is used in the training using the scaled conjugate gradient as the training algorithm. Figure 8.5 shows the performance of the forward solution.

Figure 8.5: ANN forward solution
8.2.2 Backward Solution

The backward solution is used to determine if the reservoir compaction plays a role in the production behavior. After inspecting the training data, the end plateau can be any time between 2008 and 2010. Therefore, the backward solution will utilize the production data until the end of 2010. The network is successfully developed and the testing data set has an average correlation coefficient of 0.99. Figure 8.6 shows a cross-plot of the predicted porosity and permeability multipliers between the predicted and actual data. A second neural network will utilize the whole production data, i.e., 2015. Again, the network shows excellent performance and the average correlation coefficient is 0.99. Figure 8.7 shows an example.

Figure 8.6: ANN backward solution after 2010
In general, porosity compaction has a much greater effect on oil recovery than permeability compaction. That is because the reduction in the pore volume will result in a similar increase of the hydrocarbon production. Permeability, on the other hand, represents the conduit through which the hydrocarbon passes. Its effect is mainly noticed on the well pressure, not the hydrocarbon volume. Figure 8.8 is a tornado chart that shows the effect of the ten parameters when each parameter goes from the minimum value to the maximum on the cumulative oil production.

8.3 Homogeneous Reservoir, Three Rock Regions

This case is similar to the previous case, but there are three rock regions instead of one. That means there are three compaction tables, one for each region. Each layer of the reservoir has one of the rock regions. The changes in the porosity and permeability multipliers are the same as in the previous case. The y-axis represents the five porosity (p) and permeability (k) values for the five different pressures, where the numbers 1 to 5 refer to the pressure values of 1000, 2000, 3000, 4000, and 5000 psi, respectively.
8.3.1 Forward Solution

A similar analysis from the previous case applies to this one. The only difference is in the input to the neural network. In this case, there are 30 input parameters: 5 for the porosity multipliers and 5 for the permeability multipliers for each rock region. The network performed very well in predicting the production behavior of the reservoir. Figure 8.9 shows how accurate the prediction of the network is. The average error for all testing runs is 2%.
8.3.2 Backward Solution

Similar analysis from the previous case applies here. The first network is successfully developed and the testing data set has an average correlation coefficient of 0.97. Figure 8.10 shows a cross-plot of the predicted porosity and permeability multipliers between the predicted and actual data. A second neural network will utilize the whole production data, i.e., until 2015. Again, the network shows excellent performance and the average correlation coefficient is 0.97. Figure 8.11 shows an example for one of the testing cases in the backward solution.
This case will test the network ability to perform in heterogeneous reservoirs. In this case, the reservoir is heterogeneous in both porosity and permeability. Figure 8.12 shows the permeability distribution of the top layer of the reservoir. There are three rock regions, one per layer. The uncertainty ranges in the porosity and permeability multipliers are the same as in the previous cases.
8.4.1 Forward Solution

A similar analysis from the previous case applies to this one. The production period is 2500 days. The network performed very well in predicting the production behavior of the reservoir with an average error of 3%. Figure 8.13 shows how accurate the prediction of the network is.

8.4.2 Backward Solution

Similar analysis from the previous case applies here. The first network is successfully trained using production data until 2000 days. The testing data set has an average correlation coefficient of 0.98. Figure 8.14 shows a cross-plot of the predicted porosity and permeability multipliers between the predicted and actual data. A second neural network will utilize the whole production data, i.e., until 2500 days. Again, the network shows excellent performance and the average correlation coefficient is still 0.98. Figure 8.15 shows an example.
Figure 8.13: ANN Forward Solution

Figure 8.14: ANN backward solution after 2000 days
Figure 8.15: ANN backward solution after 2500 days
Chapter 9 Tarmat Breakdown

Tarmat layers are found in many reservoirs. They usually occur at the base of the hydrocarbon accumulation, isolating the reservoir from its aquifer. Tarmat layers are almost immobile and have permeability close to zero. Tarmat can break if there is sufficient pressure differential across the layer. The breakdown of the tarmat layer can help recover some of the heavy oil and supply pressure to the reservoir through the aquifer, but it can also bring water immaturely. Geomechanical and mathematical models are usually used to predict the time and location of the breakdown. In this section, an expert system will try to detect the time and location of the breakdown when an unexpected behavior is noticed.

9.1 Reservoir Model

The reservoir model is an 11x11x7 square block model. The block dimensions are 200’x200’x30’. It consists of 7 layers. The top four contain the hydrocarbon, the 5th is the tarmat layer, and the last two are the aquifer. The reservoir is heterogeneous in porosity and permeability. The tarmat layer has a permeability of 0.1 md. Top of the reservoir is at 4990’ and the initial reservoir pressure is 3000 psi. The goemechanical properties of the reservoir rocks are assumed to be elasto-plastic. The reservoir is tested with two different completions. The first is one horizontal well completed in the top layer at the middle of the reservoir in the x-direction. The second has three vertical wells that are completed in the top three layers. Figure 9.1 shows the location of the wells for both cases.
The tarmat breakdown occurs as a result of geomechanical changes induced by the stress exerted on the tarmat layer. The following two equations are used to compute the maximum stress (Hsu, 2008) and strain of the reservoir rocks:

\[ \sigma_{\text{max}} = \frac{0.308 \times \Delta P \times L^2}{h^2} \]  

(9.1)

where \( \sigma_{\text{max}} \) = maximum stress, \( \Delta P \) = differential pressure across the grid block, \( L \) = length of the grid block, and \( h \) = thickness of the grid block.

\[ \varepsilon_{\text{max}} = \frac{\sigma_{\text{max}}}{E_s} \]  

(9.2)

where \( \varepsilon_{\text{max}} \) = maximum strain, and \( E_s \) = Young’s modulus of elasticity.

From equation 9.2, the parameters that affect the stress values are the differential pressure, length of the block, and height of the block. The length of the block is constant in this reservoir. The pressure differential does not drastically vary between the blocks. Therefore, the height of the block seems the only factor that can considerably affect the maximum stress. The thinner the block is, the greater the stress. Hence comes the idea of
reducing the thickness of one block at a time to simulate random breakdown locations. This thin layer is assigned a value of 10’. As an assumption, this thin layer will break when the maximum strain reaches a value of 0.1. This is the signal that identifies the breakdown time. After this block is identified, it is assigned a very high permeability value at the time of the breakdown to allow communication between the reservoir and the aquifer. Figure 9.2 illustrates how the tarmat breakdown can bring more energy to the reservoir by increasing the oil rate, water rate, and reservoir pressure. The study covers the period from 2000 to 2015.

![Tarmat Breakage Effect](image)

**Figure 9.2: Comparison of reservoir performance before and after tarmat breakdown**

### 9.2 One Well and One-Block Breakdown

This case aims to deploy the expert system when there is an unexpected behavior to determine if the cause is the breakdown of the tarmat layer. The reservoir is produced
through one horizontal well in the middle of layer 2. There is only one block in the tarmat
layer that is going to be broken.

9.2.1 Forward Solution

There is no automated way to identify when the thin block will reach a strain of
0.1. This process is done manually. The reservoir simulator is used to generate 50 cases
with varying thin block locations. Computation of the strain values is then done manually
in order to identify the time of the breakdown. Once this is determined, we go back to the
reservoir data file and alter the permeability of the thin block at the time of the
breakdown. The file is then submitted to the simulator to get the correct production
profile after the tarmat breakdown. In all the 50 cases, the breakdown occurs between
April 2003 and April 2004. Once all the 50 cases are altered, the construction of the
neural network forward solution begins. The inputs to the network are the location of the
thin block in terms of i and j, the breakdown time, the distance of the thin block from the
well, and the angle of the thin block from the well. The outputs to the network are the oil
production rate, water production rate, well block pressure, and cumulative oil
production. The production covers 15 years over 25 time steps, which makes the total
number of output parameters 100. The forward solution performed well in predicting the
reservoir performance. However, it struggles to match the water production profile
although it is able to predict the breakthrough time. Figure 9.3 is an example of the
performance of the forward solution.
9.2.2 Backward Solution

The backward solution uses the same 50 data sets and takes the production profile at the end of 2005, few months after the water breakthrough has been observed, and returns the location of the thin block in terms of i and j, the time of the breakdown, the distance of the thin block from the well, and the angle from the well. Here the angle is between -180 to 180. Figure 9.4 shows the performance of the five test cases.

The number of data sets in this case is quite low compared to the possible number of scenarios. To see if increasing the number of data sets can increase the accuracy of the network. 300 new data sets are generated, but instead of manually determining the time of the breakage, it was randomly assigned to be between April 2004 and April 2005. The data sets are divided into 225 sets for training, 45 for validating, and 30 for testing. The results show some improvement in Figure 9.5. Another modification to the network is done by converting the angle to 360 degrees, which resulted in even a better improvement as it can be seen in Figure 9.6.
Figure 9.4: ANN inverse solution performance with small data set

Figure 9.5: ANN inverse solution performance with larger data set
This case aims to deploy the expert system when there is an unexpected production behavior to determine if the cause is due to the breakdown of the tarmat layer. The reservoir is produced through three vertical wells. There is only one block in the tarmat layer that is going to be broken. The breakdown will occur randomly between April 2004 and April 2005. This time frame was determined based on geomechanics.

### 9.3.1 Forward Solution

300 cases are generated by the reservoir simulator. The inputs to the network are the location of the thin block in terms of i and j and the breakdown time. The outputs to the network are the oil production rate, water production rate, and well block pressure for the three producers. The production period covers 15 years over 25 time steps, which makes the total number of output parameters 225. The forward solution performed well in predicting the reservoir performance. However, it could not match the water production very accurately although it is able to predict the breakthrough time. Figure 9.7 is an example of the performance of the forward solution of wells 1 and 2.
9.3.2 Backward Solution

The backward solution network takes the production profiles for the three wells and outputs the location and time of the breakdown. Figure 9.8 is a cross-plot between the predicted and actual data. The breakdown time accuracy is within ±2 months. The accuracy of the breakdown location is within ±1 block in both the x and y directions.
9.4 Three Wells and Two-Block Breakdown

This is similar to the previous case, but there are two different blocks to break about three years apart. There are two thin blocks in the tarmat layer. The first one could break any time between December 2003 and June 2004. The second block could break any time between December 2006 and July 2007.

9.4.1 Forward Solution

A total of 300 cases are generated by the reservoir simulator. The inputs to the network are the distance of the thin block from the grid origin, the angle of the block from the origin, and the time of the breakdown. These inputs are for each thin block, which brings the total number of inputs to six. The outputs to the network are the oil production rate, water production rate, and well block pressure for the three wells. The production covers 15 years over 29 time steps, which makes the total number of output parameters 261. The forward solution performed well in predicting the reservoir performance. However, it could not match the water production very accurately although it is able to predict the breakthrough time. Figure 9.9 is an example of the performance of the forward solution for the three wells.

9.4.2 Backward Solution

There will be two neural networks: one to detect the first tarmat breakdown and the second is to detect the second breakdown. The inputs to the first network is the oil rate, water rate, and block pressure for the three wells up to the end of 2006. The outputs are the distance of the first breakdown from the origin of the grid, the angle, and the time of the breakdown. Figure 9.10 shows a cross-plot of the location, angle, and time between
the predicted and actual values. The correlation coefficients for the three parameters are 0.961, 0.988, and 0.967. The second network takes the rates and pressures up to the end of 2010 and output the distance, the angle, and the time of both breakdowns.

Figure 9.11 shows a cross-plot of the location, angle, and time between the predicted and the actual values for the two breakdowns. The correlation coefficients for the three parameters of the second breakdown are 0.837, 0.894, and 0.311. The network predicted the first breakdown more accurately, but not as accurate as the previous network. Further investigation for multiple tarmat breakdowns will be needed. However, when the output of the backward solution is validated by the forward solution, the results appear to be acceptable. Figure 9.12 shows the validation of one of the test cases of the backward solution through the forward solution.
Figure 9.10: Cross-plot of the ANN backward solution after the first breakdown

Figure 9.11: Cross-plot of the ANN backward solution after two breakdowns

Figure 9.12: Validation of the backward solution
Chapter 10 Natural Fractures

Naturally fractured reservoirs are found all over the globe. Natural fractures can enhance the well productivity and, depending on the nature of the reservoir, can be the only contributing flow paths in tight reservoirs. Here, an artificial expert system is developed to detect areas of the reservoir where there are natural fractures. It is initially believed that the reservoir is fracture-free, but there is a possibility of natural fracture existence in areas that are not covered by wells. Production profile signatures are used to identify the location of the fractures, fracture spacing, and fracture permeability.

10.1 Reservoir Model

The reservoir model is a 15x15x1 square block model. The block dimensions are 200’x200’x300’. The reservoir is tight and heterogeneous in porosity and permeability. The top of the reservoir is at 5000’ and the initial reservoir pressure is 4000 psi. The reservoir is completed with four horizontal wells producing at constant rate. There is a water aquifer at the bottom of the reservoir. A second multi-layered reservoir model is built that has four layers and the thickness of each layer is 75’. Figure 10.1 shows a top view map of the reservoir with the permeability distribution.

Natural fractures are modeled in such a way that they appear in one corner of the reservoir and extend to cover up to about quarter of the reservoir. The rest of the reservoir is still unfractured. A dual-porosity model is used to simulate the natural fractures. Natural fracture data is assumed to be taken from offset reservoirs. Figure 10.2 shows some possibilities of natural fracture location and extent. Figure 10.3 shows how natural
fractures can enhance the productivity of a well. Well-2 has seen an increase in oil and water production due to its proximity to the natural fracture area.

Figure 10.1: Top view of the reservoir

Figure 10.2: Different realization for natural fracture location and extent
10.2 One-Layered Fractured Reservoir

This case aims to deploy the expert system when there is an unexpected behavior to determine if the cause is due to the effect of natural fractures. The reservoir is produced through four horizontal wells with constant rates.

10.2.1 Forward Solution

A total of 500 cases are generated by the reservoir simulator. The inputs to the network are the quadrant where the natural fractures are located (1~4), the number of blocks in the i and j directions the fractures are occupying (3~7), the fracture permeability (50~500md), and the fracture spacing (25-200 ft). The outputs to the network are the oil production rate, water production rate, and well block pressure for the four producers. The production covers 11 years over 25 time steps, which makes the total number of output parameters 300. The forward solution performed well in predicting the reservoir performance. Figure 10.4 is an example of the excellent performance of the forward solution for the four producers. The cumulative oil production rate is calculated.
10.2.2 Backward Solution

The same data set will be used for the backward solution; the input to the network will be the production profiles of the four wells after five years of production. The outputs to the network are the fracture quadrant, extent, permeability, and spacing. The network performed great in detecting the location and the extent of the fractures. However, it predicted the fracture permeability and spacing with much less accuracy. Figure 10.5 shows a cross plot of the five output parameters of the backward solution. The regression coefficients for the quadrant, fractures in the i-direction, fractures in the j-directions, fracture permeability, and fracture spacing are 0.96, 0.98, 0.98, 0.66, and 0.72 respectively.
After performing sensitivity analysis, it turned out that varying the fracture permeability values from 50 to 500 md had little impact in the cumulative oil production. Permeability values above 100 md almost had no effect on increasing oil production. This broad range of fracture permeability has caused the network to perform weakly in regards to the fracture permeability. The expert system was then rebuilt with new ranges for the fracture permeability (20~100 md). Fracture spacing range was also reduced (10~50 ft). The network improved in its generalization capability after this modification. The regression coefficients for the five parameters are 0.90, 0.95, 0.96, 0.81, and 0.89, respectively. Figure 10.6 shows the performance of the backward solution after the modified data range.
10.3 Multi-Layered Fractured Reservoir

The same concept is applied here. However, the reservoir now has four layers instead of a single layer. Fractures can extend up to the fourth layer.

10.3.1 Forward Solution

A total of 500 cases are generated, similar to the above case. One extra parameter is added, which is the number of layers that contains the natural fractures (1~4). The network predicted the wells’ performance extremely well. Figure 10.7 shows the performance of the forward solution.

10.3.2 Backward Solution

Similar to the previous scenario, the network predicted the location and the extent of the fracture very well. It also predicted the fracture spacing satisfactorily. The fracture permeability and the number of fractured layers were predicted with less accuracy. The
regression coefficients for the six parameters (the sixth one is the number of layers) are: 0.96, 0.99, 0.99, 0.70, 0.96, and 0.87, respectively. Figure 10.8 shows the performance of the backward solution.
10.4 Fractured Reservoir with Damaged Wells

This case aims to extend the capabilities of the expert systems to predict different parameters that can act at the same time and affect the production behavior of the wells. Besides the effect of natural fractures, two of the horizontal wells are located in a damaged-prone area. This area is in the first quadrant (north-west). It is assumed that the damage, which is in the form of a skin factor, occurs after two years of production. All wells are stimulated before production and their skin factor is -3. After the second year, Well-2 and Well-5 start gaining positive skin. The role of the expert system is to identify the natural fracture location and extent and to determine if the two wells are experiencing skin that may affect their performance.

10.4.1 Forward Solution

A total of 500 cases are generated by the reservoir simulator. The inputs to the networks are the six natural fracture parameters described in the previous section. In addition, skin factors are added to the two wells for four years starting from the third year of production. There is still a possibility that the wells do not experience any damage for the first or second year. The damaged wells may gain a positive skin up to a value of 10 during four years. This will bring the skin parameters to eight and the total number of parameters for the inputs to 14. The outputs to the network are the oil production rate, water production rate, and well block pressure for the four horizontal producers. Figure 10.9 shows the performance of one of the test cases of the forward solution. The network performed very satisfactorily with an average error of 4% and the two wells are able to capture the effect of the skin over the years. In this example, Well-2 experienced a skin of
2 and lasted for three years and at the fourth year the skin jumped to 10. Well-5 skin values are -3, -1.5, 2 and 10.

Figure 10.9: Performance of the forward network

10.4.2 Backward Solution

The backward solution starts after three years of production when the first change of skin has taken place. Hence, the outputs to the network are the six parameters for the natural fractures and the skin value for each of the two wells. Figure 10.10a shows the performance of the network in predicting the natural fracture parameters. The network achieved 90% in generalization accuracy. The fracture permeability is still the least accurate parameter. Figure 10.10b shows how the network performed in predicting the skin factor for the two wells. The few number of data points might have contributed to the inaccuracy of the network prediction.
Figure 10.10a: Performance of the backward solution for the natural fractures

Figure 10.10b: Performance of the backward solution for the skin factor
After another year of production, more data became available. Two additional skin factor parameters for the additional year have been added to the backward solution network. The network prediction capabilities increased to 94% accuracy. Again the fracture permeability prediction still needs improvement. Figures 10.11a and 10.11b show the performance of the backward solution after the second change of skin. As additional data becomes available, additional skin parameters are added. Newly developed networks can then be trained to predict the new skin factor values.

Figure 10.11a: Performance of the backward solution for the natural fractures
Figure 10.11b: Performance of the backward solution for the skin factor
Chapter 11 Graphical User Interface (GUI)

11.1 Introduction

One of the objectives of creating expert systems is to provide a tool that help reservoir engineers make better decisions. These expert systems can fulfill this objective if they are presented in a form where the engineers or users can utilize it. Otherwise, the user would need some training in order to use these expert systems. These systems are introduced in a user-friendly format that enables users without prior knowledge of artificial neural networks to use these systems. For this part of the research, two graphical user interfaces have been developed. The first one is the reservoir properties determination covered in section 5.1. The second interface is for the hydraulic fractures characterization covered in section 7.4. These graphical user interfaces are developed using GUIDE, the MATLAB® graphical user interface development environment.

11.2 GUI for Determining Reservoir Properties

This tool is for the model described in section 5.1. The reservoir has a central well and four symmetrical wells on the sides. The inputs to the forward solution of the system are five reservoir properties: original oil-water contact, porosity, permeability, vertical to horizontal permeability ratio, and geometrical factor of Well-1. The outputs are the oil rate, water rate, and block pressure for wells 1 and 2. The inputs to the backward solution network are the production profiles of the two wells while the outputs are the five reservoir properties. When the expert system is launched, a window with a title asks the user to select whether to use the forward solution or the backward solution. Figure 11.1 is the main window of this GUI.
11.2.1 Forward Solution Graphical User Interface

Once the forward solution button is pressed, the following screen appears as in Figure 11.2. This is where the user inputs the five reservoir parameters to generate the oil production, water production, and block pressure of wells 1 and 2. The window will start with default values, which are changeable. If the input values are out of range, an error message will appear indicating the proper range of the values. The “Plot” button should be clicked once all the five input parameters are entered. The system will then generate the required plots for wells 1 and 2. This process is very fast and hence the user can generate several plots from different realizations in a very short time. Figure 11.3 shows how the expert system predicts the production profile based on the data input. To cross check the output of the expert system, the user can click on the “Simulate” button. What this does is call the simulator and feed it with the inputs from the user. The reservoir
simulator makes the run and generates the production profiles. The expert system then collects the data and plots them on top of the previously generated data from the expert system. Figure 11.4 shows the expert system output along with the simulator output.

Figure 11.2: Forward solution window for the reservoir properties expert system
Figure 11.3: Forward solution as predicted by the expert system
Figure 11.4: Comparison between the output of the expert system and the simulator
11.2.2 Backward Solution Graphical User Interface

The backward solution part of the expert system works a little bit differently. The user is required to load the production rates, water rates, and well block pressures for wells 1 and 2 into a text file. The expert system will then read its inputs from this text file. After that the user can click on “Calculate” button to receive the five reservoir parameters. The GUI will also display the production profile that the user has input. Figure 11.5 shows the interface of the backward solution.

Figure 11.5: Reservoir properties determination by the backward solution
The “Simulate” button will cross check the results of the expert system’s output by calling the reservoir simulator to make a run with the five reservoir properties and plot the results back on top of the existing data. The user then can determine the level of trustiness towards the expert system. Figure 11.6 shows a comparison between the expert system output and the reservoir simulator output.

![Image](image.png)

**Figure 11.6: Comparison between the output of the expert system and the simulator**
11.3 GUI for Hydraulic Fracturing Expert System

This tool is for the reservoir described in section 7.4. This is a tight reservoir with one horizontal well completed in the middle of the reservoir. After four years of production, the well is fractured. The fracture job consists of five stages. Each fracture has a different fracture length, width, and permeability. In this problem, the width and permeability are combined as one parameter called the effective permeability as described earlier. The inputs to the forward solution are the fracture half-length and effective permeability for each fracture stage. The outputs are the production profile of the well. The backward solution takes the well production profile as inputs to output the characteristics of the five fracture stages. When the expert system is launched, a window with a title asks the user to select whether to use the forward solution or the backward solution. Figure 11.7 is the main window of this GUI.

![Figure 11.7: Main window for the hydraulic fracturing expert system](image-url)
11.3.1 Forward Solution Graphical User Interface

Once the forward solution button is pressed, the following screen appears. This is where the user inputs the fracture half-length and effective permeability of the five hydraulic fractures to generate the oil production, water production, block pressure, and cumulative oil production of Wells-1. The window will start with default values, which are changeable. If the input values are out of range, an error message will appear indicating the proper range of the values. The “Plot” button should be clicked once all the ten input parameters are entered. The system will then generate the required plots for Well-1. This process is very fast and hence the user can generate several plots form different realizations in a very short time. To cross check the output of the expert system, the user can click on the “Simulate” button. What this does is call the simulator and feed it with the inputs from the user. The reservoir simulator makes the run and generates the production profiles. The expert system then collects the data and plots them on top of the previously generated data from the expert system. Figure 11.8 shows the expert system output along with the simulator output.
11.3.2 Backward Solution Graphical User Interface

The backward solution part of the expert system works a little bit differently. The user is required to load the production rate, water rate, well block pressure, and cumulative oil production for Well-1 into a text file. The expert system will then read its inputs from this text file. After that the user can click on “Calculate” button to receive the fracture half-length and effective permeability for the five hydraulic fractures. The GUI will also display the production profile that the user has input.

Figure 11.8: Comparison between the output of the expert system and the simulator
The “Simulate” button will cross check the results of the expert system’s output by calling the reservoir simulator to make a run with the ten fracture properties and plot the results back on top of the existing data. The user then can determine the level of trustiness towards the expert system. Figure 11.9 shows a comparison between the expert system output and the reservoir simulator output.

Figure 11.9: Comparison between the output of the expert system and the simulator
Chapter 12 Summary and Recommendations

12.1 Summary

In this research, expert systems are developed to help reservoir engineers make better decisions regarding their reservoirs. The first expert system can help in history matching. This tool can be used with a new reservoir model to obtain the starting parameters for the history matching process. Starting with good initial values for the history matching can save the engineers from performing tens of extra simulation runs. Also, this tool can be applied to an already history-matched reservoir model to bring the reservoir properties closer to their actual values. For more complex reservoirs, this expert system will help in history matching by reducing the uncertainty of the reservoir parameters based on the engineer’s input. The expert system utilizes artificial neural network for training and prediction. The system is composed of two parts; the first one deals with the forward solution of the problems, where the reservoir properties are fed to the network in order to obtain the production profiles of the wells. If trained successfully, this forward solution can by used as a proxy to the reservoir simulation model, where hundreds of sensitivity runs can be performed in a very short time. The second part of the expert system is the backward solution, where the production profiles of the wells are fed to the network to obtain the required reservoir properties.

Another set of expert systems is developed as a diagnostic tool to highlight the possible causes of unexpected production behavior. If the reservoir model is well history-matched, it is expected to deliver good predictions. Once the observed data from the field starts to deviate from the expected behavior, a flag is raised by the engineer. Then comes
the role of the expert systems. The reservoir engineer along with the help of the geologist and field operation personnel should use their expertise to identify the possible causes of such deviation. Their input is translated into expert systems tailored for the reservoir specific characteristics. In this research, four types of diagnostic expert systems are developed. The first tool tries to determine if the cause of the unexpected production decline is an increased skin factor or if the perforations are plugged. The backward solution part of the expert system receives the production profile and determines the associated skin factor or the reduction in the perforation productivity. A more advanced expert system can be applied if these two factors are acting at the same time. The second expert system is concerned with the hydraulic fracture characterization. After each hydraulic fracture job, the engineer designs each stage fracture to have specific permeability, length and width. Therefore, the reservoir model should reflect the performance satisfactorily. If the production profile becomes drastically different from what is expected, the expert system can be deployed to check the fracture characteristics. The system is fed with the production profile to output the fracture length and effective permeability. A more advanced system can pinpoint if any of the fractures is closing. The third expert system looks into the effect reservoir compaction of porosity and permeability on the production behavior. Reservoirs with compaction drive are modeled by including a compaction table, where multipliers of porosity and permeability vary with the pressure. The expert system helps determine those multipliers based on the production profile of the reservoir. Hence, the engineer can update his model to keep it matched and up-to-date. The fourth expert system is used with reservoirs that have tarmat layers at the base of hydrocarbon accumulation. If the tarmat layer breaks, it brings
energy to the reservoir in terms of pressure and production increase. The expert system is introduced after an unexpected water breakthrough occurs or when there is a sudden increase in the hydrocarbon production rate. Its purpose is to determine the location and time of the tar mat breakdown based on the production profile. This expert system is successful in predicting the breakdown when it first occurs. However, if there is a subsequent breakdown at another location, the network doesn’t perform that well in detecting the location and time of the second breakdown. The fifth expert system is responsible for identifying areas of the reservoir where natural fractures might exist. Based on the changes of the production profiles, this tool was able to approximately identify the location and the area of the natural fractures. Fracture spacing was also predicted with acceptable accuracy. However, the expert system was not able to predict the natural fracture permeability satisfactorily. This expert system was extended to predict the skin factors of two producers that are, in the same time, subject to the effect of natural fractures. The expert system worked similarly to the original case in terms of identifying the natural fractures and was able to satisfactorily detect the varying skin factors for the two wells. Finally, a graphical user interface (GUI) is built to provide the users of the expert systems with a user-friendly interface for adding or editing data. The interface generates the required reservoir parameters and plots different production profiles.

This research has closed the gap left by previous research. Many parameters were examined and the expert systems worked very well. Previous studies only used a few parameters. The assisted history matching expert system was extended to the prediction phase and was shown to perform satisfactorily whereas previous studies were only
concerned about achieving a good history match. More importantly, the developed expert systems showed great flexibility when handling temporal changes that occurred during the life of the reservoir.

These expert systems can serve as excellent reservoir management tools. It is worth mentioning that these expert systems should not be used as stand-alone tools. Reservoir simulators should always be referred to for critical decision-making. In the case of multiple answers given by the expert systems due to the non-uniqueness of the solution, supporting evidence from well logs, well tests, core analysis, etc., should be included in the study.

Upon the successful implementation of the assisted history matching protocol and the identification of the causes of unexpected reservoir behavior, researchers and reservoir engineers will be able to:

- Decrease the history matching time considerably and obtain reservoir parameters that are much closer to the real reservoir values.
- Keep the reservoir model up-to-date by incorporating the changes in the reservoir.
- Reduce the cost and expended manpower of running reservoir simulators.
- Apply and customize the methodology for any specific reservoir.
- Substantially decrease the requirements of running logs, core analysis and other diagnostic tools and hence reduce the operational cost.
- Have a better decision-making tool with supporting studies.
- Use this methodology as an impetus to think of other new areas of research where expert systems can be developed and applied.
12.2 Recommendations for Further Work

The following topics need to be further researched:

- Study the effect of different drive mechanisms, such as gas cap and edge water drive. This is related to the assisted history matching expert system. In this research, only compaction and bottom water drive were researched. The gas cap drive will add another dimension to the problem since it adds a third fluid phase in a free form as wells as introducing hysteresis. Edge water drive will greatly affect the boundary conditions in the reservoir simulation model and have a role on the water breakthrough time for producer wells.

- Use sensitivity analysis to reduce the number of uncertain parameters during the assisted history matching process. This is useful when there is a reservoir with many uncertain parameters. Considering too many parameters in a study requires more powerful resources in terms of computation, time, and personnel. Sensitivity analysis studies can be performed in order to eliminate the parameters that have little to no effect on the objective function.

- Enhance the tarmat expert system to deal with more than one breakdown. It was shown that the tarmat expert system performed very well when only one area of the tarmat layer broke. However, the results are not as good when another area of the tarmat layers broke. Incorporating more geomechanical data or the use of a coupled geomechanical-reservoir simulator should provide better results.

- Develop a complex expert system where several factors that may cause production behavior changes are present. There are endless possibilities that several parameters can affect the performance of the reservoir. It was shown that
the expert system could handle two parameters acting on the reservoir at the same time. A study with more parameters can greatly help engineers diagnose suspected reservoir problems, especially in the case of complex reservoirs.

• Explore reservoirs that only have injection wells, not producers. There are other types of reservoirs that can benefit from the flexible expert systems. Steam injection or CO₂ sequestration are a couple of examples.
References


Vitae

Nader BuKhamseen

Nader BuKhamseen was born in Khobar, Saudi Arabia on January 11, 1978. After finishing high school in 1995, he joined Saudi Aramco where he was awarded a scholarship to study petroleum engineering at King Fahd University of Petroleum and Minerals in Dhahran, Saudi Arabia. He earned his Bachelor’s of Science degree with honors in 2000. He won the local SPE student’s paper contest and the second place in the regional SPE student’s paper contest.

In July 2000, Nader joined Aramco’s Reservoir Description and Simulation Department where he worked as a petroleum database analyst. He then had one-year long assignments as a production engineer, drilling engineer, and log analyst. In 2004, he obtained a scholarship from Saudi Aramco to complete his advanced degree from Heriot Watt University in Edinburgh, United Kingdom. In November 2005, he earned his Master’s of Science degree in petroleum engineering.

Upon returning to Saudi Aramco, Nader worked as a reservoir simulation engineer for two years. He then moved to the Reservoir Management Department where he became part of the intelligent field team. In 2009, he got another scholarship for the Ph.D. degree. He started his degree at the University of Texas at Austin and after two years he transferred to the Pennsylvania State University. He successfully defended his dissertation on May 29, 2014 and earned his Doctor of Philosophy degree in Energy and Mineral Engineering with the option of Petroleum and Natural Gas Engineering in August 2014. After graduation he will resume his role with Saudi Aramco as a reservoir simulation engineer.