Carbonate Reservoir Characterization Based on Integration of 3-D Seismic Data and Well Logs Using Conventional and Artificial Intelligence Approaches

A Thesis by
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Reservoir characterization refers to the process of inferring information about reservoir properties from seismic data. Obtaining accurate information about the reservoir properties such as porosity, lithology, and permeability is an essential objective in seismic exploration, especially in new areas that lack well control. This thesis contributes to the integrated analysis of 3-D seismic data and well logs for a square study area in the eastern province of Saudi Arabia, allowing improved understanding, interpretation and characterization of an upper Jurassic carbonate reservoir. The thesis focuses on the analysis aspect of the 3-D post-stack for seismic reservoir characterization through the interpretive use of seismic attributes using different approaches.
The thesis can be divided into two key stages. First, a pre-processing stage covering the quality-control of the seismic data sets, calculation of seismic attributes, flattening of the 3-D seismic cube along target horizons, and calibration between seismic data and well-logs. The instantaneous attributes (amplitude, phase and frequency) of seismic data can be calculated and used, along with relative acoustic impedance, as the main seismic attributes to elucidate reservoir characteristics and to reduce exploration risk.

Secondly, a main analysis stage develops and tests different effective techniques for analyzing seismic data and conducting reservoir characterization. Five main tools have been developed in-house through MATLAB coding to obtain accurate spatial mapping of the reservoir most important properties that can be used for modelling and simulation which provide better understanding of the reservoir under investigation. This particular choice of tools should work properly for post-stack data.

The following summarises and highlights the main contributions of the thesis. First, is to enhance the predictive performance of the conventional multiple linear regression method through coupling information from cluster analysis. Then, I introduce the ‘grey system theory’, which was originally developed in China and has seen little application in geophysics, as a new tool for hydrocarbon exploration; I propose its use for detecting hydrocarbon anomalies associated with the carbonate reservoir. Next, I implement a Kohonen self-organizing map (SOM) neural network for clustering the reservoir heterogeneity (main lithofacies), and enhance the method by feeding it multiple attributes as an input. Furthermore, I estimate reservoir porosity and permeability by implementing a supervised back-propagation neural network. Finally, a hybrid approach that combines an artificial neural network and a fuzzy interface is developed for estimating well lithology from well logs.
Different informative results were drawn from this study which can be summarised as follow:

The result indicates that the upper part of the ZOI is more porous than the lower part. The reservoir porosity is ranging from 5% to around 28% within the ZOI with an average porosity of approximately 15%. In addition, the reservoir permeability shows ranging values from less than 500md to 2500md. The zone of interest (ZOI), in general, is divided into three distinct subzones ranging in their reservoir quality. This study indicates that the upper zone, middle zone, and lower zone of the ZOI are featured by (medium porosity / high permeability), (high porosity / low permeability), and (low porosity / medium permeability), respectively. The mapping result of the reservoir lithofacies spatial distribution indicates that there are at least nine major lithofacies deposits. Wackestone, packstone, grainstone, and mudstone are four types of the main lithofacies within the study area.

The main conclusions drawn from this study can be summarised as follow:

(a) The main aim of this study was achieved by estimating the reservoir porosity and permeability, as well as, clustering the reservoir lithology into the main lithofacies through ‘multiple linear regression’ and ‘artificial neural networks’ methods which proved (after validation) to be a powerful technique for characterizing reservoirs, especially the carbonate reservoir.

(b) The grey system theory has been introduced to the reservoir study field and ‘grey attribute’ is proposed to highlight hydrocarbon accumulations after finding good correlation with the producing wells in the area.

(c) An innovative implementation of ART2 neural network has been proposed to estimate the intra-well lithology by a hybrid-system that combines the neural network classification with the fuzzy interface for
a better result. The final result indicated that the zone of interest (ZOI) is dominated by grainy packstone, wackestone/packstone, and muddy wackestone for the top, middle, and bottom subzones, respectively.

Different regional maps have been generated for the reservoir main properties (porosity and permeability), lithofacies, and hydrocarbon accumulation. Validation of the result has been performed taken as a measure of the method performance and accuracy. The correlation coefficient was used to represent the success ratio. For example, the success ratio for predicting the reservoir porosity were 79% and 85% for the improved multiple linear regression method and back propagation neural network method, respectively. The result of each method has contributed substantially to achieve the main objectives of this study not only in obtaining better understanding of the reservoir spatial distribution for future planned drilling in the area, but also offering new input for remodelling the reservoir and updating the simulation.

Student Name: Abdulrahman AlMoqbel
Thesis Supervisor: Professor Yanghua Wang
I dedicate this work to my

Beloved mother,

whom has been providing me with encouragement, inspiration, and support to successfully accomplish different achievements particularly this PhD degree.

I also dedicate this work also to my beloved father, brothers, sisters, wife and kids.

I dedicate this thesis also to the memory of loved ones who I lost through the years.
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LIST OF SYMBOLS AND ABBREVIATIONS

AGO: Accumulated Generation Operation
AI: Artificial Intelligence
ANN: Artificial Neural Network
API: American Petroleum Institute (oil classification)
ART: Adaptive Resonance Theory
AVO: Amplitude Variation with Offset
BMU: Best Matching Units
BPNN: Back-Propagation Neural Network
BS: Black System
C-ART2: Category ART2
CC: Correlation Coefficient
CGCA: Chinese Grey System Association
CTT: Complex Trace Theory
DMD: Data Mining Discovery
DMO: Dip Move Out
DT: Sonic Log
EDA: Exploratory Data Analysis
FFNN: Feed-Forward Neural Network
FL: Fuzzy Logic
G&G: Geological and Geophysical
GA: Genetic Algorithm
GDR: Generalized Delta Rule
GIT: Grey Incidence Theory
GR: Gamma Ray Log
GRA: Grey Relation Analysis
<table>
<thead>
<tr>
<th>Acronym</th>
<th>Full Form</th>
</tr>
</thead>
<tbody>
<tr>
<td>GS</td>
<td>Grey System</td>
</tr>
<tr>
<td>GST</td>
<td>Grey System Theory</td>
</tr>
<tr>
<td>HC</td>
<td>HydroCarbon</td>
</tr>
<tr>
<td>HI</td>
<td>Hydrocarbon Indicator</td>
</tr>
<tr>
<td>HST</td>
<td>Highstand System Tract</td>
</tr>
<tr>
<td>HT</td>
<td>Hilbert Transform</td>
</tr>
<tr>
<td>IAGO</td>
<td>Inverse Accumulated Generation Operation</td>
</tr>
<tr>
<td>IEEE</td>
<td>Institute of Electrical and Electronics Engineers</td>
</tr>
<tr>
<td>IMP</td>
<td>Acoustic Impedance</td>
</tr>
<tr>
<td>INNS</td>
<td>International Neural Networks Society</td>
</tr>
<tr>
<td>INV</td>
<td>Inversion</td>
</tr>
<tr>
<td>KDD</td>
<td>Knowledge Discovery in Databases</td>
</tr>
<tr>
<td>KSOM</td>
<td>Kohonen Self-Organizing Map</td>
</tr>
<tr>
<td>LAS</td>
<td>Log ASCII Standard format</td>
</tr>
<tr>
<td>LST</td>
<td>Lowstand System Tract</td>
</tr>
<tr>
<td>LTM</td>
<td>Long-Term Memory</td>
</tr>
<tr>
<td>MIT</td>
<td>Massachusetts Institute of Technology</td>
</tr>
<tr>
<td>ML</td>
<td>Machine Learning</td>
</tr>
<tr>
<td>MLP</td>
<td>Multi-Layer Perceptron network</td>
</tr>
<tr>
<td>MLR</td>
<td>Multiple Linear Regression</td>
</tr>
<tr>
<td>MSE</td>
<td>Mean Square Error</td>
</tr>
<tr>
<td>NNJ</td>
<td>Neural Networks Journal</td>
</tr>
<tr>
<td>NPHI</td>
<td>Neutron-Porosity Log</td>
</tr>
<tr>
<td>PDP</td>
<td>Parallel Distributed Processing</td>
</tr>
<tr>
<td>PE</td>
<td>Processing Element</td>
</tr>
<tr>
<td>PERM</td>
<td>Permeability Log</td>
</tr>
<tr>
<td>QC</td>
<td>Quality Control</td>
</tr>
<tr>
<td>R-ART2</td>
<td>Raw ART2</td>
</tr>
<tr>
<td>RAP</td>
<td>Relative Amplitude Preserving</td>
</tr>
</tbody>
</table>
RC: Reflection Coefficients  
RGU: Representative Genetic Units  
RHOB: Density Log  
SAA: Seismic Attributes Analysis  
SC: Soft Computing  
SCT: System Control Theory  
SDM: Steepest Descent Method  
SPD: Stability-Plasticity Dilemma  
SOM: Self-Organizing Map (SOM) Neural Network  
ST: Synthetic Trace  
STM: Short-Term Memory  
SVM: Support Vector Machines  
U-Matrix: Unified distance-Matrix  
VP: Vigilance Parameter  
Vp: P-wave Velocity (compressional velocity)  
Vs: S-wave Velocity (shear velocity)  
VSP: Vertical Seismic Profile  
WS: White System  
ZOI: Zone Of Interest
LIST OF PARAMETERS AND VARIABLES

CHAPTER 2:

\( z(t) \) .......................... The Complex Trace.
\( x(t) \) .......................... The Real Part of a Complex Trace.
\( y(t) \) .......................... The Imaginary Part of a Complex Trace
\( a(t) \) .......................... The Instantaneous Amplitude.
\( \phi(t) \) .......................... The Instantaneous Phase.
\( F(t) \) .......................... The Instantaneous Frequency.
\( I \) .......................... Imaginary Number.
\( \Phi(z) \) .......................... The Porosity Expressed as a Function of Depth.
\( \Delta t \) .......................... The Well Log Sonic Transit Time.
\( \Delta t_m \) .......................... The Matrix Transit Time.
\( \Delta t_f \) .......................... The Fluid Transit Time.

CHAPTER 3:

\( \rho \) .......................... The Density.
\( V \) .......................... The Wave Propagation Velocity.
\( R \) .......................... The Normal Incident Reflectivity for a Seismic Wave Front
\( A_i \) .......................... The Displacement Amplitude of the Incident Wave.
\( A_r \) .......................... The Displacement Amplitude of the Reflected Wave.
\( z_1 \) .......................... Depth 1.
\( z_2 \) .......................... Depth 2.
\( T_{1-2} \) .......................... The Integrated Sonic (Vertical Travel Time) Curve.
* ....................... The Convolution Operation.
\( W \) ..................... The Wavelet.
\( ST \) ....................... The Seismic Trace.
\( RC \) ....................... The Reflection Coefficient Series.

CHAPTER 4:

\( P \) ......................... The Property to be Estimated (e.g. porosity).
\( A_m \) ......................... The Seismic Attributes.
\( M \) ......................... Number of Seismic Attributes.
\( \sigma \) ......................... Poisson Ratio.
\( k \) ......................... Bulk Modulus.
\( \mu \) ......................... Rigid Modulus.
\( E \) ......................... Young Modulus.
\( \lambda \) ..................... Lame’s Constant.
\( \rho \) ......................... Density.
\( Vp/Vs \) ................... Lithology Indicator Ratio.

CHAPTER 5:

\( x^0(i) \) .................. The Grey System Original Data at Time \( i \).
\( x^1(i) \) .................... The Grey System New Generated Sequence at Time \( i \).
\( a \) and \( u \) ................. The Grey Least Square Parameters.
\( B \) ......................... The Grey Matrix.
\( y_N \) ....................... The Grey Output.
\( x^1(k) \) .......... The Predictive Value at Time \( k \).
\( x^0(k+1) \) ............... The Predictive Value at Time \( k+1 \).

CHAPTER 6:

\( t \) ......................... Time.
\( x(t) \) ....................... An Input Pattern to SOM Network.
\( c(x) \) ...................... The Winner Node of the SOM Network.
\( m_i(t+1) \) ............... The Updated Weights of the Vector at the Current Iteration.
\( m_i(t) \) ..................... The Weights of the Vector at the Previous Iteration.
\( h_{ci}(t) \) .................. The Gaussian Neighborhood Function in SOM Network.
\( \alpha(t) \) .................. The Learning Rate.
\( \sigma(t) \) ................... The Radius of the Neighbourhood Function at Time

CHAPTER 7:

\( (x_{p1}, x_{p2}, ..., x_{pN}) \) .......... The Input Signals to the BPNN.
\( (w_{j1}, w_{j2}, ..., w_{jk}) \) .......... The Synaptic Weights of Neuron \( j \).
\( NET_{pj} \) ................. The Linear Combiner Output.
\( \phi_{pj} \) .................... The Threshold.
\( \varphi \) ....................... The Activation Function.
\( y_{pj} \) ....................... The Output Signal from the Neuron.
CHAPTER 8:

\( n \)  
Number of Input Units in \( F_1 \) Layer of an ART2 Network.

\( m \)  
Number of Cluster Units in \( F_2 \) Layer of an ART2 Network.

\( a, b \)  
Fixed Weights in the \( F_1 \) Layer of an ART2 Network.

\( c \)  
Fixed Weight Used in Testing For Reset in ART2.

\( d \)  
Activation of Winning \( F_2 \) Unit in ART2.

\( e \)  
A Small Parameter.

\( \theta \)  
Noise Suppression Parameter.

\( \alpha \)  
Learning Rate.

\( \rho \)  
Vigilance Parameter.

\( t_{ji} \)  
Top-down Weights in ART2.

\( b_{ij} \)  
Bottom-up Weights in ART2.

\( s_i \)  
The Input Signal in ART2.

\( u_i, w_i, p_i, x_i, q_i, v_i \)  
The Activation Units in ART2.

\( f(x) \)  
The Activation Function in ART2.

\( y_i \)  
The Output Vector in ART2.

Appendix 7A:

\( \delta_{pk} \)  
The Error at a Single Output Unit in BPNN.

\( p \)  
The \( p^{th} \) Training Vector in BPNN.

\( k \)  
The \( k^{th} \) Output Unit in BPNN.
\( y_{pk} \) ................. The Desired Output Value from the \( k^{th} \) Unit.

\( o_{pk} \) .................... The Actual Output Value from the \( k^{th} \) Unit.

\( E_p \) ....................... The Error Function in BPNN.

\( \nabla E_p \) .................... The Gradient of Error Function in BPNN.

\( \frac{dE_p}{dw_{kj}} \) .............. The Gradient of the Error Function with respect to a weight.
CHAPTER 1 INTRODUCTION

“I have been impressed with the urgency of doing. Knowing is not enough; we must apply. Being willing is not enough; we must do.”

(Leonardo da Vinci)

1.1 STATEMENT OF THE PROBLEM

Due to the economical value of oil and gas accumulations in a reservoir, one of the main objectives in the petroleum industry is to locate and map hydrocarbon anomalies suitable for drilling. Discovering hydrocarbons by seismic exploration is a primary yet not simple task entailing four stages preceded in the following order: data acquisition, data processing, data interpretation, and finally well proposition and drilling. The outcome of drilling is either a discovery or a failure, where the result is usually credited to or blamed on how well the reservoir was characterized before drilling the proposed well. The process of inferring information about the reservoir properties from seismic data is commonly known as “seismic reservoir characterization”. The characterization of a reservoir is achieved through data mining, which is the process of exploring and analysing large quantities of data to discover meaningful patterns and rules (Zangel and Hannerer, 2003).

In general, there are two main types of petroleum reservoirs: carbonate and clastic. The former is usually composed of dolomite and limestone, while the latter is composed of sandstone. Compared to a clastic reservoir, a carbonate reservoir is more heterogeneous system (Akbar et al., 1995). Due to this heterogeneity, the process of characterizing a carbonate reservoir is more
complicated, especially when conventional methods are used (Hallenburg, 1998).

The most accurate estimates or measures of reservoir properties can be obtained by laboratory investigation. Alternative options include the analysis of well logs and the description of core data. However, all these options are considered to be local measurements that may not reflect the reservoir behaviour as a whole.

1.2 MOTIVATIONS

This study is motivated by the need for better understanding of the heterogeneity and properties distribution of the carbonate reservoir through integrating and analysing the post-stack data sets. Unlike well data which provide high vertical resolution (0.1-1.0 m) and usually are available at sparse horizontal resolution, seismic data can offer 3-D spatial coverage of the reservoir properties within a larger area of investigation. The spatial resolution and areal coverage of seismic data are much greater than those of well data; therefore, 3-D seismic surveys are the mainstay of the petroleum industry.

In the oil and gas exploration industry, the large majority of exploration data are obtained by reflection seismology, which provides a practical method of obtaining high-quality images of the subsurface and yields valuable information that could lead to the discovery of hydrocarbon accumulations. Further, seismic data provide not only a structural and stratigraphic framework, but also contain information about the spatial variability of certain important physical properties (e.g., porosity, permeability, lithology and fluid content) (Brown, 1999). These subsurface reservoir rock and fluid properties, which can be hidden within the seismic data, provide valuable information for characterizing a reservoir and/or highlighting hydrocarbon accumulations when integrated with well data. From an economic perspective, this desirable yet
hidden information is very important not only for developing and managing the reservoir, but also for lowering the drilling risk and ensuring economically viable exploration.

Many successful case studies correlating reservoir properties with seismic attributes have been reported: for example, Hardage et al. (1998 and 1996), Gastaldi et al. (1997), and Raeuchle et al. (1997). The development of seismic attribute analysis for characterizing reservoirs started with single attribute analysis, and was later developed by combining multiple attributes. Interpretation of seismic data independently of other data sources has evolved to incorporate multiple attributes for more reliable predictions, such that the computation and analysis of multiple attributes is the favoured approach (Alam et al., 1995).

In addition to the clues to lithology typing which is offered by the use of multiple seismic attributes, these attributes also facilitate structural interpretation, as well as, recognition of seismic stratigraphy. Recent advances in data analysis algorithms have allowed much improved accuracy of reservoir models. Thus, modelled reservoirs can be used with more confidence to simulate the behaviour of fluids within the reservoir under different circumstances and to choose the optimal extraction techniques for maximizing production (Brown, 2001). With advances in analysis tools and computing power, a variety of powerful new techniques are becoming increasingly widely used to take advantage of seismic attribute data, with greater success than conventional techniques. The use of seismic attributes to predict the regional distribution of reservoir properties within the study area by correlating well data with seismic data has gained popularity, and encompasses a number of different techniques such as geostatistical analysis (Hirsche et al, 1997), multiple linear regression and neural networks (Russell et al, 1997). All of these techniques require the geophysicist to make inferences from the seismic data corresponding to a small number of wells and then to extrapolate these
inferences to a larger population, which is assumed to represent the sample (Kalkomey, 1997). This work will contribute to: reduced drilling risks, exploration of more fields, and enhanced development of existent fields.

1.3 MAIN AIM AND OBJECTIVES

The main aim of this thesis is to characterize a carbonate reservoir through obtaining accurate reservoir properties and reliable spatial mapping of the reservoir heterogeneity. The characterization of the reservoir can be achieved using different analysis tasks such as classification, estimation, segmentation and description. First, the integration of the seismic data with the well data is completed, and then the implementations of state-of-the-art numerical analysis techniques are coded. The aim can be addressed through five key objectives:

1) Calculate sub-surface seismic attributes which contain valuable information for characterizing the reservoir;

2) Integrate the sparse geological observations (hard-data) and the dense seismic data (soft-data) by performing accurate calibration to ensure accurate modelling of the reservoir’s lateral distribution;

3) Map selected reservoir properties such as porosity, and lithology by studying and developing some of the newest and most efficient techniques;

4) Propose a new approach for highlighting the reservoir hydrocarbon distribution; and

5) Analyze, validate and interpret the results obtained by the different proposed techniques for better understanding and characterization of the reservoir under study.
1.4 SCOPE OF THE THESIS AND CONTRIBUTIONS

This thesis enhances our understanding and interpretation of the reservoir under investigation. The reservoir case study is a carbonate reservoir, located in the eastern province of Saudi Arabia.

Although the literature reveals a diverse range of approaches for analysing the post-stack and well logs, this thesis focuses on the following five techniques: multiple linear regression (MLR), grey system theory (GST), Kohonen self-organizing map (KSOM) which is an unsupervised neural network, a supervised back-propagation neural network (BPNN), and an innovative approach that combines artificial networks from the adaptive resonance theory (ART) and a fuzzy logic interface. I have coded these methods using MATLAB.

The following is a brief description of the contributions for each of the techniques towards analysing and characterising the reservoir.

METHOD 1: Multiple Linear Regressions (MLR)

MLR is one of the most popular statistical methods for analysing dependencies between data sets. This method is commonly used in studying and characterizing reservoirs. An interesting part of this analysis is that the estimation of the reservoir properties uses multiple seismic attributes instead of a single attribute. According to Alam et al. (1995), multiple seismic attributes analysis is able to generate more accurate results than a single attribute analysis. The method is a generalization of curve-fitting in multi-dimensional space; it allows the creation of a spatial algebraic formula that can be used to calculate values needed to fill gaps in a data set (Gelman and Hill, 2007).
Instead of employing conventional multiple regression, this thesis couples regression with cluster analysis to improve the accuracy of the prediction.

**METHOD 2: Grey System Theory (GST)**

GST was developed by Professor Julong Deng from China over 25 years ago. The theory was tested and implemented in different fields of study. This thesis introduces and tests GST for a seismic exploration application. A ‘grey attribute’ is proposed in this thesis for highlighting the reservoir hydrocarbon accumulation after obtaining a good correlation between the well production-classifications and the proposed grey attribute.

Therefore, this thesis proposes GST as a new tool for highlighting hydrocarbon accumulations in a reservoir, especially in carbonates.

One of the most efficient approaches for fast computation and reliable-results in complex systems is called “*Artificial Intelligence (AI)*”. AI can be defined as “*a collection of new analytic tools that attempts to imitate thought*” (Mohaghegh, 2000). Over the past two decades, AI has drawn the attention of many researchers in the petroleum industry, and has been applied to address several fundamental problems (Sandha et al., 2005).

**Artificial neural networks** are one category of the artificial intelligence tools. Artificial neural networks (ANNs) are generally defined as being “*any computing architecture that is composed of massively parallel interconnections of simple neural processors*” (Lau, 1991).

ANNs have been utilized by geoscientists in a variety of science and engineering fields. The artificial neural network approach has been widely accepted as a powerful tool for many petroleum exploration tasks including reservoir characterization and properties estimation from well logs (Huang et
al., 1996; Huang and Williamson, 1997; Zhang et al., 2000; Helle et al., 2001; Fruhwirth et al., 2006). A comprehensive review of the ANN approach is included in Appendix 1.A. Appendix 1.B has a summary table of the advantages and disadvantages for different artificial neural networks. ANNs are characterised by their ability to model the heterogeneous, complex reservoir system, and their ability to predict non-linear relationships between well data (well logs) and seismic attributes. ANNs are distributive, parallel systems of immense power for solving pattern recognition problems.

Methods 3, 4 and 5 (below) all employ artificial intelligence analysis to study the target reservoir.

METHOD 3: Self-Organizing Map (SOM) Neural Network

SOM is an unsupervised neural network algorithm that projects high-dimensional data onto a lower dimensional (two-dimensional map). The projection preserves the topology of the data so that similar data items will be mapped to nearby locations on the map. This type of neural networks not only reduces the dimensionality of large data sets, but also visualizes the hidden structures within the data by grouping similar data items together. In many studies and applications, SOMs have proved to be an excellent tool for visualising and thus understanding the data. SOM is therefore considered as one of the best solutions for classifying large data sets.

The Kohonen self-organizing map (KSOM) algorithm is implemented in this study to cluster the reservoir’s spatial heterogeneity. The algorithm is then enhanced to process multiple input attributes (instead of a single attribute). The result of the analysis illustrates the spatial clustering of the reservoir’s main lithofacies.
METHOD 4: Back-Propagation Neural Network (BPNN)

BPNNs are generally recognised as one of the most powerful artificial neural networks, and have been widely used in many applications for finding non-linear relationships between the input attribute(s) and the target property. This thesis implements a BPNN for estimating the reservoir’s most important properties: porosity and permeability. This type of network is characterised by its ability to learn, to generalize (adapt), and to be error-tolerant. The network employs an advanced problem-solving algorithm that relies on complex connections between various data sets. Many different tasks can be performed by this algorithm, including classification and estimation.

This thesis uses BPNN for estimating the porosity and permeability of the reservoir spatially at the reservoir different levels.

METHOD 5: Hybrid Approach (ART with Fuzzy Interface)

A hybrid approach is developed for determining lithology at well locations. Both an artificial neural network and a fuzzy inference system are combined by utilising the well logs and knowledge (about data) for predicting the lithology.

This thesis develops an innovative and hybrid approach which incorporates the knowledge about the reservoir at a fuzzy logic interface with ART2 networks clustering to identify the different lithofacies of a given well. Table 1.1 highlights the analysis type for each of the implemented methods.
1.5 OUTLINE OF THESIS

Chapters 2 and 3 represent the pre-analysis stage, while the analysis stage is divided into five parts, described in Chapters 4 to 8, which respectively cover each of the techniques used in this study.

The remainder of the thesis is organised as follows. Chapter 2 describes the study area, the data sets, and the target reservoir; it also covers calculation of the main seismic attributes which are used in the techniques developed in this thesis. Chapter 3 mainly deals with the data set calibration process.
Chapters 4 and 5 present MLR and GST methods, respectively. Chapters 6, 7, and 8 are devoted to the artificial intelligence approaches, namely KSOM, BPNN, and ART2s-Fuzzy neural networks, respectively. Finally, conclusions and recommendations are given in Chapter 9.

A section containing the main terminologies is attached at the end of the thesis. The first appearance of each terminology is marked by **bold** font within the thesis context. A summary of the workflow and key contributions resulting from the thesis is presented in Table 1.2.
<table>
<thead>
<tr>
<th>Stages</th>
<th>Pre-Analysis</th>
<th>Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Reviewing, Editing, and Quality Controlling the Data</td>
<td>Method 1: Multiple Linear Regression</td>
</tr>
<tr>
<td></td>
<td>Horizon Picking</td>
<td>Method 2: Grey System Analysis</td>
</tr>
<tr>
<td></td>
<td>Seismic Attributes Calculations</td>
<td>Method 3: Kohonen Self-Organizing Map</td>
</tr>
<tr>
<td></td>
<td>Seismic Data Flattening</td>
<td>Method 4: Back-Propagation Neural Network</td>
</tr>
<tr>
<td></td>
<td>Data Sets Calibration</td>
<td>Method 5: Adaptive Resonance Theory</td>
</tr>
</tbody>
</table>

**Intra-well Method 5: Adaptive Resonance Theory**

**Method 3: Kohonen Self-Organizing Map**

**Method 4: Back-Propagation Neural Network**

**Method 2: Grey System Analysis**

**Method 1: Multiple Linear Regression**

**Table 1.2** A summary of the workflow and key contributions resulting from this thesis.
CHAPTER 2  DATA SETS: SEISMIC ATTRIBUTES AND POROSITY LOGGING

“All truths are easy to understand once they are discovered; the point is to discover them.”

(Galileo Galilei)

This chapter focuses on describing the data sets and calculating the seismic attributes used in the thesis. There are two main data sets for the area under study: a 3-D post-stack seismic volume and a suite of well logs. The study area is located in the Middle East and covering part of the eastern province of Saudi Arabia. Information about the study area and the target reservoir, as well as, description of the main inputs used by techniques applied in later chapters, are covered in this chapter. Four main seismic attributes were considered: instantaneous amplitude, instantaneous phase, instantaneous frequency and relative acoustic impedance. From the seismic volume, three instantaneous attribute cubes were calculated following the complex trace theory suggested by Taner et al. (1979), while the porosity logs at the well locations were calculated using Wyllie’s equation.
2.1 INTRODUCTION

**Porosity** is one of the fundamental parameters used for reservoir characterization and hydrocarbon volumetric determination (Moore, 2001). Accurate estimates of porosity minimise risk and cost associated with the *exploration* and *development* of oil fields (Foster et al., 1993; Rapoport et al., 1997; Avseth et al., 2001).

A reservoir’s properties can be revealed by seismic attribute analysis employing several different geophysical techniques: amplitude variation with offset (AVO), inversion (INV), artificial neural networks (ANN) and seismic attributes analysis (SAA). Each method has its advantages and limitations. In general, the AVO and INV methods are mostly implemented through pre-stack analysis; on the other hand, ANN and SAA are more commonly implemented on post-stack data. Despite a number of different approaches having been suggested to estimate reservoir porosity, sophisticated techniques that have been proven to work successfully in clastic reservoirs have not yet been as successful in carbonates (Eberli et al., 2004).

The main objectives of this chapter are to define and quality control (QC) the data sets, and to calculate relevant attributes of the data in preparation for their use as input into the subsequent analysis stage (see Chapter 3). Brief reviews of the study area and its reservoir geology are provided in the following two sections (Sections 2.2 and 2.3). Next, Sections 2.4 and 2.5 discuss the calculation of input seismic attributes and the porosity at well locations, respectively. Section 2.6 presents and analyzes the results. Finally, conclusions are summarized in Section 2.7.
2.2 STUDY AREA

The study area is a 40 × 40 km² square in the eastern province of Saudi Arabia. The data sets used in this study consist of a 3-D seismic volume and a suite of well logs. The acquisition parameters of the seismic data are included in Appendix 2.A.

There are eight wells within the study area: A01, A03, A09, A15, A17, A18, A20 and A21 (Figure 2.1). The inline and crossline that pass through the wells are listed in Table 2.1. The production of the wells ranges from high to low. The available well logs include sonic properties, density (RHOB) and gamma ray (GR) data. Neutron-porosity (NPHI) logs are available in three wells: A15, A18 and A20. Permeability (PERM) logs are also available in certain wells. Table 2.2 shows the availability of the main logs. All the wells data were in Log ASCII Standard (LAS) format. Logs were plotted versus depth. A visual inspection was performed to confirm that all curves look reasonable and free of unexpected spikes or washouts. Log analysis is preformed to understand the zone of interest (ZOI); deriving the lithology as part of the petrophysical investigation is essential (Rider, 1996). In general, the quality of the log data is very good. Some encountered quality problems include: (1) different sampling rates (e.g., one or two sampling per foot), (2) different logging runs (for different depth zone, or re-run for the same zone), and (3) sometimes, uneven scales between the different runs.

The seismic data are amplitude-preserved and time-migrated; specifically, they comprise a RAP (relative amplitude preserving)-DMO (dip move out)-migrated post-stack volume. The cube represents 800 ms of time (Z-axis), from 700 ms to 1500 ms. There are 401 inlines oriented west to east (parallel to the
X-axis) and 401 crosslines oriented south to north (parallel to the Y-axis). The
time sample interval is 4 ms. The zone of interest (ZOI) is 44 ms long, from
924 ms to 968 ms below the reservoir top pick. One of the most critical factors
affecting the use seismic data in reservoir studies is resolution (Brown, 1999).

**Seismic resolution** is the ability to distinguish individual feature from an
observed seismic event (Sheriff, 1985). The seismic data quality at the top-
reservoir level is very good. Figure 2.2 demonstrates the quality of the data.
Figure 2.1  (a) A global location map and (b) a base map of the study area showing well locations and two seismic lines through Well A15 (map view).
<table>
<thead>
<tr>
<th>Well</th>
<th>Inline</th>
<th>Crossline</th>
</tr>
</thead>
<tbody>
<tr>
<td>A01</td>
<td>167</td>
<td>345</td>
</tr>
<tr>
<td>A03</td>
<td>105</td>
<td>306</td>
</tr>
<tr>
<td>A09</td>
<td>222</td>
<td>370</td>
</tr>
<tr>
<td>A15</td>
<td>207</td>
<td>224</td>
</tr>
<tr>
<td>A17</td>
<td>278</td>
<td>96</td>
</tr>
<tr>
<td>A18</td>
<td>166</td>
<td>88</td>
</tr>
<tr>
<td>A20</td>
<td>248</td>
<td>302</td>
</tr>
<tr>
<td>A21</td>
<td>87</td>
<td>20</td>
</tr>
</tbody>
</table>

Table 2.1 The inline number and crossline number for each of well locations.
Figure 2.2 The seismic data of quality lines through Well A15: (a) Inline 224 in the West-East direction and (b) Crossline 207 in the South-North direction. Both seismic sections show the reservoir-top pick and the Well A15.
penetration. The x-axis is the distance in kilometres and the y-axis is the two-way travel time in milliseconds.

<table>
<thead>
<tr>
<th>Sequence</th>
<th>Well</th>
<th>DT (S-wave)</th>
<th>NPHI</th>
<th>RHOB</th>
<th>Perm</th>
<th>GR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>A01</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>2</td>
<td>A03</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>3</td>
<td>A09</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>4</td>
<td>A15</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>5</td>
<td>A17</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>6</td>
<td>A18</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>7</td>
<td>A20</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>8</td>
<td>A21</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td>*</td>
</tr>
</tbody>
</table>

Table 2.2 The main six well logs for the wells in this study. They are (from left to right): P-wave sonic, S-wave sonic, neutron-porosity, density, permeability, and gamma ray.

2.3 CARBONATE RESERVOIR

2.3.1 Depositional Setting

Porosity is affected by the stratigraphic setting and the depositional facies (deposits) of a carbonate reservoir. Carbonate facies are more difficult to image seismically than clastic facies (Castagna, 2001). Carbonate rocks lack bedding and have higher seismic velocities than clastic sediments, as well as, having lower acoustic impedance contrasts within a platform succession (Read, 1985). The carbonate platform geometry forms complex structures.
with steep dips and usually contains evaporites (Schuelke and Rick, 2003). In order to map the porosity regionally and to generate meaningful interpretations of the estimated regional porosity maps, the basic depositional setting of the carbonate model is studied and described below.

One of the key processes affecting the carbonate (porosity) is the transgression and regression of sea level (Jacquin et al, 1991). Transgression and regression are defined as 'long-term sea rise' and the 'long-term sea fall', respectively. The highstand system tract (HST) causes shelf flooding, so carbonate sedimentation is the greatest during such flooding (Gadallah and Fisher, 2005). In the lowstand case (lowstand system tract (LST)), as the sea level falls, the land is exposed, which allows the high-energy erosional processes to dominate. This environment is characterized by the deposition of grain-supported facies (Gadallah and Fisher, 2005). On the other hand, in the highstand case, the land is immersed by water, and the energy is low on the ramp and medium at the shoreface. This environment is characterized by the deposition of mud facies.

In general, the main elements of a depositional carbonate system are ramp, shelf, reef and lagoon (Figure 2.3) (Schuelke and Rick, 2003). One of the most common hydrocarbon exploration targets is the reef depositional setting, which occurs in shallow marine environments with organic-dominated facies, and provides the best environment for high-porosity facies because of the good accommodation space (Read, 1985).

Unlike clastic reservoirs which are usually well-behaved and laterally predictable, lateral facies in carbonate reservoirs are harder to predict. Carbonate reservoirs face more challenges than clastic reservoirs (Table 2.3).
Figure 2.3 A 2-D sketch model showing the main deposits associated with sea-level fall (lowstand) and sea-level rise (highstand) in the carbonate depositional system. The deep sea deposits are dominated by mud, while grainstone dominates the shallow deposits. The reef facies is one of the most important carbonate reservoir features and forms as sheets dominated by coral (high organic content), which makes this facies a good target in hydrocarbon exploration.
Predicting lateral facies changes is a challenge. Facies changes are typically “well-behaved” and laterally predictable.

Boundaries can be extremely heterogeneous and unpredictable. Identification of reservoir boundaries is not a big challenge.

Carbonate reservoirs are controlled by diagenetic changes. Clastic reservoirs are controlled by depositional environment.

Porosity and permeability in carbonate can be strongly dependent on diagenesis. Porosity and permeability in clastic follow facies boundaries.

Similar rock properties between rock types (porous carbonate and shale), where could be interpreted as gas charged reservoir. Distinct rock properties between rock types.

Table 2.3 Five main challenges associated with the study of carbonate reservoirs (left column), in comparison to clastic reservoirs (right column).

2.3.2 Reservoir Geology

The study area is located in eastern Saudi Arabia; covering a small portion of the northern part of Ghawar Field. This field is the world’s largest and most prolific oil field, and produces 30° - 31° API oil from the Arab-D carbonate reservoir; it covers a region of approximately 250 km × 30 km (Lindsay et al., 2008). The field accounts for more than half of the cumulative oil production of Saudi Arabia. According to Lindsay et al. (2008), the field has more than 300 m (984 ft) of structural closure where the reservoir stratigraphically comprises the D member of the Arab Formation and the upper part of the Jubaila Formation (Figure 2.4). The formation consists of four geographically widespread carbonate-evaporite cycles, or members (Cantrell and Hagerty,
1999), which comprise a series of carbonate and anhydrite sequences. Each of the main elements required for favorable hydrocarbon occurrence are present: source, reservoir, trap and seal rocks. According to Cantrell and Meyer (2000), the formation was deposited on a shallow marine (carbonate) shelf 150 million years ago, when a major seaway separated the African and Eurasian crustal plates before the opening of the Atlantic Ocean.

This study focuses on the lowest carbonate member (the oldest), which is of Upper Jurassic age. It is overlain by Arab C-D anhydrite, which is more than 25 m (82 ft) thick and acts as a seal for hydrocarbons. The reservoir has an average porosity of more than 12%. The reservoir comprises an approximately 100 m (328 ft) thick carbonate succession, comprising limestone with 15-20% dolomite and exhibiting an overall increase in dolomite content with depth (Cantrell and Hagerty, 1999). Dolomitization is widespread in the fine-grained rocks, where the dolomites appear to have originated from the diagenesis (Powers, 1962; Sahin and Saner, 2001) by the alternation of pre-existing limestone (Cantrell and Meyer, 2000). The upper half of the reservoir is of high quality, whereas the lower half contains interbeds of high and relatively low to non-reservoir quality (Cantrell et al., 2001). Grainstones dominate the upper section of the reservoir, whereas wackestone and fine-crystalline dolomitic rocks dominate the lower units (Hughes, 1996). Vertical fractures occur within the dolomite and most of the fractures are filled with calcite, dolomite or anhydrite cement, therefore affecting the local permeability (Cantrell and Hagerty, 1999).
### Figure 2.4

Generalized Upper Jurassic stratigraphic sequence. The reservoir of interest is the lowermost carbonate unit (bordered in red) of the Arab Formation.
2.4 INPUT ATTRIBUTES

Seismic attributes have been employed as a tool in the interpretation of seismic data. Seismic attribute analysis in petroleum exploration was first used in the 1970s and 1980s, following the development of complex trace theory (CTT) in the early 1970s. Seismic attributes have become an integral tool in the interpreter’s arsenal because of their discriminatory properties that are useful for revealing hidden information and performing useful classifications. Most of the original seismic attribute analyses are based on the Hilbert transform (HT) and are based on the instantaneous amplitude, instantaneous phase and instantaneous frequency (Pennington, 2001; Campbell et al., 2008).

Geological interpretation of seismic data is commonly done by analyzing patterns of seismic amplitude, phase and frequency in map and section views across a prospect area. Although many seismic attributes have been utilized to emphasize geologic targets and to define critical rock and fluid properties, these three simple attributes – amplitude, phase and frequency – remain the mainstay of geological interpretation of seismic data (Barnes, 2007; Brown, 1999).

Four main attributes are used in this study: the three listed above, plus acoustic impedance. A brief review of these seismic attributes is provided in the following subsections.

2.4.1 Definition

Over 100 different attributes have been developed for the purpose of seismic data interpretation. Seismic attributes are derived from seismic data and are used to predict the distribution of physical properties of the reservoir. The term
‘seismic attribute’ has been defined in the literature by several authors, but is typically defined as “being the set of parameters contained within a seismic data set that help to predict the distribution of a reservoir’s physical properties” (Coren et al., 2001). Sheriff and Geldart (1994) defined a seismic attribute as “a measurement based on seismic data, such as amplitude envelope (reflection strength), instantaneous phase, instantaneous frequency, seismic velocity”.

2.4.2 Classification

The literature contains a variety of different classifications of seismic attributes. Some of the seismic attributes are based on the physical relationship between seismic wave propagation properties and reservoir rock properties. According to Brown (1995, 1996), seismic attributes are generally classified based on the main information that can be obtained from them; this information can include time, frequency, amplitude and attenuation. Chen and Sidney (1997) classified attributes as being section-based, event-based and volume-based. Another classification of attributes is based on the interpretive significance that they represent, and comprises two main categories: physical attributes and geometrical attributes (Taner et al., 1994). The instantaneous attributes (which are mainly used in this study) belong to the physical attributes category. As a broad generalization, time-derived attributes provide structural information; amplitude-derive attributes provide stratigraphic and reservoir information; while, frequency and attenuation attributes are not widely used (Brown, 1999).
2.4.3 Advantages and Limitations

Studies have shown that hydrocarbon-saturated porous rocks absorb higher frequencies, and generate a low frequency response (Barnes, 1992). However, a low frequency response is seen from many other rock types with no hydrocarbon saturation. In addition, bright spot and dim spot seismic reflections have been associated with the presence of gas. However, there are also many other cases where the bright and dim spot anomalies are caused by the velocity distribution and structural features.

Seismic reflections show a reversal of polarity when the presence of gas causes the P-wave velocity in the reservoir to decrease relative to the surrounding formation. Conversely, the polarity of reflections is positive when the presence of gas causes the P-wave velocity in the reservoir to increase relative to the surrounding formation. However, this velocity distribution can occur without the presence of gas. In such situations, caution is required when interpreting the attributes and carrying out additional investigation.

Traditional seismic analysis methods for characterizing the reservoir have been associated with disadvantages such as lengthy analysis requirements, and complicated data collection and analysis methods that may or may not perform well in different reservoir types, also taking into consideration that seismic data processing can induce or remove attribute anomalies.

2.4.4 Calculations

The instantaneous attributes which are used in this study, were first computed from seismic data using theory that had been developed for electrical engineering applications (Taner et al, 1979; Bracewell, 1965). The basis of the
instantaneous attributes is the **complex trace analysis**. Seismic attributes analysis in petroleum exploration was first used in the 1970s and 1980s following the development of complex trace theory. This theory is a powerful tool which facilitates the derivation of seismic attributes using the Hilbert transform (Robertson and Nogami, 1984). Complex seismic trace analysis is one of the most popular methods in computing post-stack seismic attributes (Barnes, 2007). A **complex trace** \( z(t) \) has two parts: the **real part** (seismic trace) and the **imaginary part** (quadrature trace).

\[
    z(t) = x(t) + iy(t) \quad \text{.................................. (2.1)}
\]

where the real \( x(t) \) and imaginary \( y(t) \) traces are identical, except for being phase shifted by \(-90^\circ\) (Taner et al., 1979) (Figure 2.5), and \( i = \sqrt{-1} \) is the imaginary number. The imaginary part of a complex trace is the Hilbert transform of the **seismic trace** (Rene et al., 1986); the derivation is attached in Appendix 2.B.

Instantaneous amplitude \( a(t) \), instantaneous phase \( \phi(t) \) and instantaneous frequency \( w(t) \) are major attributes that can be computed from a complex trace. At any point on a seismic trace, the instantaneous attributes describe a sinusoid that locally matches the trace. These attributes are calculated using the following equations:

\[
    a(t) = \sqrt{x^2(t) + y^2(t)} \quad \text{.................................. (2.2)}
\]

\[
    \phi(t) = \tan^{-1}\left[\frac{y(t)}{x(t)}\right] \quad \text{.................................. (2.3)}
\]

\[
    w(t) = \frac{d}{dt}\phi(t) \quad \text{.................................. (2.4)}
\]

Many attributes can be derived from these basic three; the new attributes are
usually products of the existing three attributes (Barnes, 2007).
Rewriting equation (2.1) in terms of the envelope \(a(t)\) and the instantaneous phase \(\phi(t)\), as follows:

\[
z(t) = a(t) \exp(i\phi(t)), \quad \text{.................. (2.5)}
\]

Equation (2.5) can also be expressed as:

\[
z(t) = a(t) \cos(\phi(t)) + ia(t) \sin(\phi(t)), \quad \text{............... (2.6)}
\]

Complex seismic trace analysis treats a seismic trace as the product of two independent and separable functions: instantaneous amplitude and cosine of the instantaneous phase (Figure 2.6), while the quadrature trace is the product of the amplitude envelope (another name for the instantaneous amplitude) and the sine of the instantaneous phase.

They are termed ‘instantaneous’ to highlight their property of being a concise and quantitative description of a seismic wave at any given time, and each of these attributes has a waveform shape (White, 1991). The instantaneous amplitude represents the magnitude of the reflection, the phase describes the polarity, and the frequency defines the time period between zero crossings (Taner et al., 1979).

More specifically, the instantaneous amplitude represents the envelope of the seismic trace; Barnes (1991) defined it as “the maximum value that the seismic trace can attain under a constant phase rotation”. The instantaneous amplitude is a measure of reflection strength and is one of the most commonly used attributes to quantify reservoirs (Meyer et al., 2001). The instantaneous phase is the phase angle required to rotate the trace to the maximum (Engelhard, 1996), the instantaneous frequency defines the times of zero crossings (Barnes, 1992), and the relative impedance is a quantitative representation of the media's elastic
properties. The benefits of using the acoustic impedance (IMP) data in the multiple attributes analysis for characterizing the reservoir are numerous (Latimer et al., 2000). Opposed to the seismic reflection data which is an interface property, IMP is a layer property that makes it useful not only for estimating reservoir properties, but also for direct geologic (stratigraphic) interpretation.

Color-encoded displays of attribute values have aided the interpretation of seismic data during the analysis of stratigraphy and hydrocarbon accumulations (Taner et al., 1979), but their most useful application has been in techniques such as multiple regression and artificial neural networks. In these cases, the 3-D seismic attributes often yield more information than the 2-D data because they can be viewed at the reservoir level over a larger area. Further, the 3-D seismic attributes complement the well data and therefore play an important role in characterizing and describing the reservoir heterogeneity. It is recommended to use those seismic attributes that have a justifiable relationship with reservoir property to be considered as candidates for predictors (Hart, 1999). These four attributes are commonly used when characterizing reservoirs, as a means of making qualitative inferences involving rock and fluid properties. Table 2.4 shows some of the reported significance for these attributes. The instantaneous amplitude is often used as the base with other attributes to isolate bright spots and dim spots; it is also one of the useful attributes for identifying AVO anomalies. The instantaneous phase is often used with other attributes as a hydrocarbon (HC) indicator, since HC often cause local phasing (Barnes, 2007). The instantaneous frequency is commonly used to estimate seismic attenuation; oil and gas reservoirs usually cause drop-off of high-frequency components. The relative impedance has been demonstrated as one of the best attributes for quantitative reservoir characterization (Gastaldi et al., 1997).
Figure 2.5  A sketch of the orientation showing the - phase shift between the real part and the imaginary part of a complex trace.
Figure 2.6 A sketch of a complex trace simplifying the physical meaning of the instantaneous amplitude and instantaneous phase.

Table 2.4 Some geologic significance of the attributes used in this study.

<table>
<thead>
<tr>
<th>Geologic Significance</th>
<th>Seismic Attributes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Instantaneous amplitude</td>
</tr>
<tr>
<td>Lithological contrasts</td>
<td>*</td>
</tr>
<tr>
<td>Bedding continuity</td>
<td>*</td>
</tr>
<tr>
<td>Bed thickness</td>
<td>*</td>
</tr>
<tr>
<td>Gross porosity</td>
<td>*</td>
</tr>
<tr>
<td>Fluid content</td>
<td></td>
</tr>
</tbody>
</table>

2.5 WELL POROSITY ESTIMATION

The porosity of a rock sample can be determined from a measurement of its bulk density (Bradley, 1992). Alternatively, porosity can be determined from
an acoustic log based upon the measurement of the travel time of an acoustic wave in the zone of interest. The sonic log is porosity log that measure the interval –transit time (DT, delta, or Δt) of a compression sound wave travelling through the reservoir (or ZOI) along the axis of the borehole. The interval transit time is dependent upon both porosity, and lithology. Therefore, a formation matrix interval transit time known to derive sonic porosity by Wyllie’s formula. Therefore, porosity logs can be derived from sonic logs at well locations using Wyllie’s Equation (Dvorkin and Nur, 1998; Dvorkin et al, 2000):

\[
\Phi(z) = \frac{\Delta t - \Delta t_m}{\Delta t_f - \Delta t_m} \quad (2.7)
\]

where \(\Phi(z)\) is the sonic-derived porosity expressed as a function of depth, \(\Delta t\) is the well log sonic transit time, \(\Delta t_m\) is the matrix transit time and \(\Delta t_f\) is the fluid transit time.

NPHI logs (available for three of the wells in the area) were utilized to evaluate the prediction accuracy of Wyllie’s equation in estimating the porosity. Zooming in on the reservoir zone, Figure 2.7 (a) shows a good match between the calculated porosity and the NPHI logs, yielding correlation coefficients of 98%, 97% and 94% for wells A15, A18, and A20, respectively. The cross-plot between the calculated porosity and the NPHI logs for wells A15, A18, and A20 is shown on Figure 2.7 (b). With such close match between the calculated porosity and the NPHI porosity for these three wells, I used Wyllie’s equation to calculate the porosity for the other wells.
(a)
Figure 2.7  (a) A comparison between the calculated porosity (black) and the Nphi (gray) logs for Wells A15, A18 and A20. The ZOI is between the two blue lines; (b) A cross-plot between the calculated porosity and the NPHI logs for Wells A15, A18, and A20. The Correlation Coefficient (CC) between the calculated porosity and the NPHI log is labeled for each of the wells.
2.6 RESULTS

Here I use the four attributes described above to estimate the reservoir porosity, based on the inter-relationships between each seismic attribute and porosity as revealed by cross-plotting. Figure 2.8 shows the calculated complex trace and vertical patterns of the four attributes for Well A15. In a 3-D view, Figure 2.9 compares the calculated complex trace to Taner et al. (1979)'s sketch of the complex trace. The zone of interest of the calculated complex traces for the eight wells is highlighted (solid curve) in Appendix 2.C.

The porosity logs were converted to time domain for cross-plotting with the seismic attributes (Figure 2.10). The zone of interest (ZOI) is represented by 12 time samples in the time domain. The comparison and cross-plot in time domain between the calculated porosity and the NPHI log for the three wells indicated similar correlation coefficient as that obtained in the depth domain (Figure 2.11). Figure 2.12 (a and b) show statistical information about the porosity at the well locations. Cross-plotting between the porosity and the four attributes at the zone of interest did not show any clear (linear) relationship (Figure 2.13). A careful investigation to understand the relationship between the different time samples at the different well locations was needed first, by cross-plotting, then by performing a clustering analysis (see Chapter 4).
Figure 2.8 The first panel is the real and imaginary parts of the calculated complex trace at Well A15. The following four panels (from left to right) are the four main seismic attributes used in this study: the instantaneous amplitude, the instantaneous phase, the instantaneous frequency, and the acoustic impedance. The zone of interest is bordered by the blue lines.
Figure 2.9 (a) The complex trace and its components (real and quadrature) as derived from Taner et al. (1979), and (b) A 3-D view of the calculated complex trace at Well A15.
Figure 2.10 The calculated porosity logs at the eight well locations. The x-axis is the calculated porosity; the y-axis is the two-way travel time in milliseconds. The top of the reservoir is marked in blue at each of the well locations.
Figure 2.11  A comparison (left column), and cross-plot (right column) between the calculated porosity and the NPHI logs in the time domain for Wells A15, A18, and A20, respectively.
Figure 2.12 (a) The average porosity of the zone of interest at the well locations; (b) the histogram of porosity at the well locations.
Figure 2.13  Cross-plot of porosity with each of the four attributes in the ZOI at Well A15 showing no clear relationship between the calculated porosity and the attributes.
2.7 CONCLUSIONS

The study area is a small part of the largest oil field in the world which is located in the eastern region of Saudi Arabia. This chapter sheds light on the importance of the hidden seismic attributes in unveiling valuable information about the carbonate reservoir under investigation. Due to their significance in revealing important reservoir properties, the following four attributes were selected: instantaneous amplitude, instantaneous phase, instantaneous frequency and acoustic impedance. The instantaneous attributes were calculated utilizing the complex trace theory. These four attributes are used in later chapters as the main input for some of the developed techniques in this thesis. Porosity, one of the main reservoir properties, has been calculated in this chapter. The porosity logs were calculated using Wyllie’s equation, and then compared with the available NPHI logs (three out of the eight wells) to evaluate the result. The correlation (in time and depth domains) was 98%, 97%, and 95% for Wells A15, A18, and A20, respectively. Given this high correlation, Wyllie’s equation was used also to estimate the porosity for the remaining five wells in the area. The porosity statistics in the zone of interest (ZOI) indicates an average porosity of approximately 12%.
CHAPTER 3   DATA CALIBRATION

“The mere formulation of a problem is far more essential than its solution, which may be merely a matter of mathematical or experimental skills. To raise new questions, new possibilities, to regard old problems from a new angle require creative imagination and marks real advances in science.”

(Albert Einstein)

One of the fundamental steps in seismic data analysis is the seismic-to-well ties. Well ties provide an important linkage between the recorded seismic data and the physics occurring behind it. Understanding the relationship between the reservoir and fluid properties measured in the wells and their presentation in seismic data is crucial to prediction of the reservoir and fluid properties away from the well location based on the seismic response. Therefore, data calibration at well location is an important process for reservoir characterization. The calibration follows six main steps: (a) reading and quality controlling the input data, (b) calculating the reflectivity logs at depth, (c) converting the reflectivity data from the depth domain to the time domain, (d) fitting the calculated reflectivity data to the seismic cube and calibrating the two data sets, (e) extracting a wavelet, and (f) finally generating the synthetic seismograms at well locations.
3.1 DATA PREPARATION

Accurate data calibration leads to accurate time and/or depth structure maps which bring out the (structural) details corresponding to the hydrocarbon bearing units of the reservoir. Good correspondence between the seismic and well data also aids in identifying/mapping the geological environment of the zone of interest (ZOI) (Singh et al., 1996). In most cases, lateral variations of porosity cannot be estimated from measurements made at sparsely located wells. Therefore, the integration of 3-D seismic data with petrophysical measurements of the wells can significantly improve the spatial description of porosity, because it provides a dense and regular areal sampling of the reservoir properties.

When dealing with seismic data and well data collectively, data integration is one of the main tasks required to accurately characterize a reservoir. In general, there are three ways to link the two data sets: using stacking velocities derived from seismic data, generating vertical seismic profiles (VSP), and using synthetic seismograms derived from seismic data. This chapter integrates the data sets through the last of these three approaches, namely synthetic seismograms, which is a useful way and widely used tool for tying seismic time to log depth.

Figure 3.1 illustrates the general workflow used to calibrate the two data sets. The quality of the input data is an important factor in obtaining accurate results in the calibration process. Here, reference is made to a total of eight wells distributed throughout the domain of the 3-D seismic survey of the study area (Figure 3.2). Borehole data for these wells consist of several wireline logs. A comprehensive calibration process requires two main log types: sonic and density. After reviewing and reformattting the logs, each log is examined individually, to identify obviously erroneous values of sonic properties or
density that would create artificial acoustic impedance contrasts that could result in the creation of false reflections in the synthetic seismograms. Sonic and density logs of reasonably good quality are available for all the wells, with an example shown in Figure 3.3. The seismic data quality is presented in Figure 3.4, which shows inline 224 and crossline 207, that both pass through Well A15.
Figure 3.1  The workflow of the main calibration processes.
Figure 3.2  A basemap (map-view) of the study area showing the well locations and two cross-sections (in blue) through Well A15: the inline and the crossline. The x-axis and y-axis are the distance in kilometres.
Figure 3.3 Sonic log (left) and density log (right) at Well A15. The y-axis is the depth in meters. The ZOI is shown between the two horizontal blue lines.
**Figure 3.4** Seismic data quality is shown by two intersecting seismic arrays through Well A15: (a) inline 224 and (b) crossline 207.
3.1.1 Reservoir Top-horizon Seismic Picking

The geological marker of the reservoir top in the wells was first extended from the well locations into the seismic cube. Then, the top of the reservoir was seismically picked at every 10th inline and crossline trace in the seismic profile to finally generate a regional grid covering the study area; this top-reservoir pick was picked as a trough through the seismic sections. Figure 3.5 shows the resulting two-way travel time map (time structure map) of the reservoir top, revealing the general structural trends within the study area – in particular the highs (red structures) and lows (blue structures).
Figure 3.5 A map-view of the time structure map of the top-horizon seismic pick of the reservoir. The high and low structures are shown by the red and blue colors. The x-axis and y-axis are the distance in kilometres.

3.1.2 Seismic Data Flattening

One of the main objectives of seismic interpretation is to extract hidden reservoir features from the seismic data. One commonly used interpretation technique that helps in this respect is to flatten data on a given horizon (Lomask and Claerbout, 2001). **Seismic flattening** is a valuable technique that serves for a variety of purposes and objectives. For example, it is used for better understanding the geological history, identifying geological features and removing folding effects, thus aiding the interpretation of seismic **horizons**, ...
computation of interval thickness and reconstruction of the paleosurface (Lee, 2001). In general, the ability to flatten the data could be a powerful tool in automating interpretation. For instance, meandering channels clearly appear on flattened data, therefore making it easier for data interpretation.

Bienati et al. (1999), and Bienati and Spagnolini (2001) have developed an auto-picking method for seismic data flattening. The flattening process utilizes the top-horizon pick of the reservoir to apply a time shift to the seismic cube. Data flattening is applied in this study to reduce the difficulty and complexity of calibration. Data flattening is used for better handling of the calibration procedure because the un-flattened volume requires separate analyses for each well location due to the different penetration depths of the reservoir at different well locations. On the other hand, once the seismic volume is flattened, the top-horizon pick of the reservoir can be considered as a regional reference for the ZOI at all well locations. Figure 3.6 shows the results of the flattening process for inline 224 and crossline 207 that pass through Well A15. The ZOI is 44 ms below the flattening datum, which is fixed at 924 ms.
Figure 3.6 The results of flattening profiles through Well A15: inline 224 (top) and crossline 207 (bottom). The flattening datum is at 924 ms (horizon-top pick) and the ZOI is 44 ms below this datum.
3.2 ACOUSTIC IMPEDANCE AND REFLECTIVITY

Unlike conventional seismic data, which represent an acoustic image of the subsurface rather than an absolute stratigraphic or geological measurement, seismic acoustic impedance data permit discrimination between the different lithological units of the ZOI by virtue of their unique acoustic signature (Lucia, 1995).

For the purpose of matching the known geology at the well locations to the seismic data, and for calibration of the two data sets, sonic and density logs are used to calculate acoustic impedance and reflectivity.

The sonic tool offers very close measurements with a sample rate of half a foot, thus giving instantaneous measurements. The instantaneous velocity can be calculated by the derivative of the distances travelled, with respect to travel time, by the following equation, which can be approximated by the difference:

$$V_{\text{inst}}(z) = \frac{dz}{dt} \approx \frac{\Delta z}{\Delta t} \quad \text{......................... (3.1)}$$

The depth sampling of the tool is fixed every half a foot, so the velocity becomes the inverse of the slowness:

$$V_{\text{inst}}(z) = (\text{slowness})^{-1} \quad \text{.......................... (3.2)}$$

This velocity is used in combination with the density log to calculate the acoustic impedance (IMP). The computation of the acoustic impedance from the seismic trace can be described by the generic term ‘seismic inversion’. Inversion is “a procedure that allows the geology to be inferred from its image measurements and a priori knowledge” (Dimri, 1992; Ursin et al, 1999). This computation is merely the transformation of a band limited reflection sequence into an acoustic solution (Aki and Richards, 1980). The impedance of an elastic
medium is the ratio of stress to particle velocity (Aki and Richards, 1980) and is given by:

\[ \text{IMP} = \rho V \]  \hspace{1cm} (3.3)

where \( \rho \) is the density and \( V \) is the wave propagation velocity.

The final geological model is one of an infinite set of models, all of which fit the observed response. Assuming that the layers are **homogeneous**, **isotropic** and elastic, the normal incident reflectivity (\( R \)) for a seismic wave front travelling from Medium 1 to Medium 2 is the ratio of the displacement amplitude, \( A_r \), of the reflected wave to that of the incident wave, \( A_i \), and is given by:

\[ R_{12} = \frac{A_r}{A_i} = \frac{\text{IMP}_2 - \text{IMP}_1}{\text{IMP}_2 + \text{IMP}_1} = \frac{\rho_2 V_2 - \rho_1 V_1}{\rho_2 V_2 + \rho_1 V_1} \]  \hspace{1cm} (3.4)

This expression of the **reflection coefficient** is obtained when the particle displacements are measured with respect to the wave vector (equivalent to the slowness vector or direction of propagation). The displacement is considered to be positive when its component along the interface has the same phase (or same direction) as the component of the wave vector along the interface. For P-waves, this means that positive displacement is along the direction of propagation. Thus, a positive reflection coefficient implies a reflected compression and a negative reflection coefficient implies a phase inversion (Sheriff and Geldart, 1994).

The average velocity as a function of depth is obtained by integrating the measured one-way travel time. From the average velocity, the acoustic impedance of each layer is obtained using the density log data. The reflection coefficient can then be calculated using the acoustic impedance of each layer. Next, the reflection coefficients are transformed from the depth domain to time domain in three steps (Figure 3.7). First, the reflectivity in the depth domain is converted to irregularly-spaced samples of reflectivity in the time domain. The
The integrated sonic curve is calculated using the travel time information. The vertical travel time \((T_{1-2})\) between depth \((z_1)\) and depth \((z_2)\) can be expressed as an integral:

\[
T_{1-2} = \int_{z_1}^{z_2} \frac{dz}{V_{int}(z)} \tag{3.5}
\]

where \((T_{1-2})\) is also known as the 'integrated sonic'.

The next step is to interpolate between the reflectivity samples. The reflectivity is then uniformly resampled to match the sampling rate of the seismic cube data. The resulting reflectivity in the time domain is then calibrated to fit the seismic cube and to tie in the well marker with the top horizon picks on the seismic section.
Figure 3.7 A sketch of the depth to time conversion process.
3.3 WAVELET EXTRACTION

Knowledge of the propagating wavelet is the main objective of estimating the reflectivity series from the seismic trace. Any given trace in the seismic cube is considered to be the result of a convolution operation between two time series: a propagating wavelet and the earth reflection coefficient series. The wavelet in the seismic data must be fully characterized so that it can be collapsed to a single spike. Therefore, careful wavelet shaping of the 3-D post-stack traces is needed, which is achieved by utilizing all the available well information. To generate the reflection coefficient series from the seismic trace in an inverse operation, a wavelet is needed for deconvolving the trace. This inversion is a two-step process: (1) estimating the seismic wavelet, and (2) using the wavelet to estimate the seismic reflectivity. Accurate wavelet estimation is absolutely critical to the success of any seismic inversion. The wavelet can be calculated using a range of different methods, such as statistical calculations or from sonic data for a nearby well.

In this study, sonic data are available at well locations, so the reflection coefficient is first calculated at these well locations.

The wavelet extraction technique can be applied within several time windows along the trace, yielding different wavelets at different depths (Dimri, 1992). When a number of different wavelets are available, the usual procedure is to use a representative wavelet. This can be chosen by visual inspection or by averaging over all the extractions. One of the purposes of wavelet processing is to broaden the bandwidth and enhance the resolution of the seismic data. Wavelet processing provides a significant gain in the interpretability and resolution of the seismic data (Hansen et al, 1994). These improvements increase confidence and detail within the ZOI. In addition, the wavelet
processing allows better interpretation of structural (subsurface) features. Because the seismic traces are known to have zero phase, the formation tops are easily and directly transferred from well data to seismic data via the synthetic seismogram.

For comparison between the seismic traces of the input wells before and after wavelet processing, a synthetic seismogram was generated at the well locations that allows visual correlation.

### 3.4 SYNTHETIC SEISMOGRAM

The tie between the wells and seismic data is the most critical step in the reservoir study and interpretation process. This study uses the synthetic seismogram approach to tie the two data sets. A synthetic seismogram is a forward modeling tool to simulate the seismic response from well data. It thus provides the link between the well data and the seismic data, yielding a useful method for correlating geological information from well logs with seismic data. The well log synthetic seismogram and the seismic data (at or near the well) should correlate because they are generated by the same geology (i.e., the same reflection coefficients (RC)). The typical solution for correlating synthetics to seismic data is to extract the wavelet from the seismic data and convolve this wavelet with the RC series to generate the synthetics. A synthetic trace (ST) is constructed by convolving the reflection coefficient (RC) at each boundary with the seismic wavelet (W) using the following convolution model (Sheriff, 1992):

\[ ST = RC \ast W + n \]  

where \( n \) is noise.

The convolution operation (*) is a mathematical function used to determine how the signal (wavelet) interacts with the layer of the earth as modelled by the
reflection coefficient series (Oldenburg, 1983). In the time domain, it is simply the response resulting from the replacement of the RC at each boundary with a scaled version of the wavelet. In the frequency domain, it is the response resulting from the multiplication of the wavelet by the RC at each boundary (Oldenburg, 1983). Synthetics are usually generated with constant or minimum phase wavelets. The minimum phase approach is recommended to match dynamite or airgun data, and a zero or 90-degree phase should be chosen for vibrators (Ewing and Caran, 1982). The synthetics reveal the detailed waveform and amplitude characteristics of the reflectors near the target (ZOI) caused by the surrounding lithology.

3.5 RESULTS

The available suites of logs, mainly sonic and density, at the well locations, were used to calculate the acoustic impedance and reflectivity logs at the well locations. Figure 3.8 shows the four logs (sonic, density, acoustic impedance and reflectivity) at Well A15.
Figure 3.8  Well logs for Well A15. From left to right: sonic, density, impedance and reflectivity. The y-axis is the depth in meters. The ZOI is between the two blue horizontal lines.

The reflectivity logs were converted from the depth domain to time domain after calculating the integrated sonic curve (depth-time curve); Figure 3.9 shows the integrated sonic log for Well A15. Next, the reflectivity was re-sampled uniformly to match the sampling rate of a seismic trace (blue curve in Figure 3.10). The calculated reflectivity logs were calibrated (the red curve in Figure 3.10) to fit the seismic cube such that they correspond closely with the well markers at the top horizon picks in the seismic sections, to provide the confidence which is needed for the interpretation in this study. Figure 3.11
shows the result of the depth-to-time conversion of the reflectivity (blue curves) for all the wells; the calibrated reflectivities for each of the wells are overlaid by the red curves. As shown in Figure 3.11, the reservoir has a different depth in each of the wells. The seismic cube was then flattened to a common reference level, in this case the top reservoir pick (flattening datum fixed at 924 ms), to facilitate analysis of the ZOI. Each of the wells was processed to fit the seismic cube and to tie the seismic reference-pick (Table 3.1). Figure 3.12 shows the final selected reflectivity logs at the well locations, which are calibrated and referenced to the top-reservoir pick. The ZOI is 12 samples (44 ms) below the reference datum.
Figure 3.9 The sonic log and the calculated integrated sonic log at Well A15. The zone of interest is between the two blue horizontal lines. The y-axis is the depth in meters.
Figure 3.10  The blue curve is the reflectivity in time domain after conversion from the depth domain. The red curve is the calibrated reflectivity that fits the seismic cube.
Figure 3.11 The flattening reference level (thick blue line) through the reflectivity of the wells. It shows different penetration depth to the zone of interest for each well.

<table>
<thead>
<tr>
<th>Well</th>
<th>Final selected vector</th>
<th>Time sample</th>
<th>Time (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A01</td>
<td>86 (111:196)</td>
<td>166</td>
<td>664</td>
</tr>
<tr>
<td>A03</td>
<td>73 (21:93)</td>
<td>76</td>
<td>304</td>
</tr>
<tr>
<td>A09</td>
<td>128 (82:209)</td>
<td>137</td>
<td>548</td>
</tr>
<tr>
<td>A15</td>
<td>71 (88:158)</td>
<td>143</td>
<td>572</td>
</tr>
<tr>
<td>A17</td>
<td>71 (134:204)</td>
<td>189</td>
<td>756</td>
</tr>
<tr>
<td>A18</td>
<td>70 (128:197)</td>
<td>183</td>
<td>732</td>
</tr>
<tr>
<td>A20</td>
<td>100 (30:129)</td>
<td>85</td>
<td>340</td>
</tr>
<tr>
<td>A21</td>
<td>69 (33:101)</td>
<td>88</td>
<td>352</td>
</tr>
</tbody>
</table>

Table 3.1 Adjustment data for each of the wells. Three important information for each well are: the final selected vector (the second column), its number of samples (the third column), and the equivalent time in milliseconds (the fourth column).
Figure 3.12  The reference datum through the wells after flattening the seismic data. The ZOI is 44 ms (12 time samples) below the flattened reference.

Wavelets were extracted from the seismic traces at the eight well locations, using well acoustic impedances computed from two main logs (sonic and density). Extracted wavelets were then convolved with the reflectivity logs to generate the synthetics, and found to be close to zero phase and spatially stable (Figure 3.13). Wavelet processing was performed for the entire 3-D seismic survey region over a time window spanning the Upper Jurassic. Deconvolution of the seismic trace by the reflectivity series produces the wavelet. Because the quality of the well data was considered to be reliable, these variations were not thought to arise from problems with the wells, and instead were attributed to naturally occurring spatial variability, intrinsic to the seismic wavelet.
Figure 3.13 The wavelet in the time (top) and frequency (bottom) domains. An extracted wavelet was convolved with the reflection coefficient series to generate the synthetics.

Because the entire calibration process hinged on the well ties at the eight well locations, the synthetic seismograms were generated at the well locations by convolving the wavelet with the respective seismic traces. The synthetic seismogram at Well A15 showed a good tie to the real seismic data (Figure 3.14), with a correlation coefficient between the measured seismic trace and the synthetic of 68%. The correlation coefficient increased to 79% if only the ZOI, from 924 ms to 968 ms, was considered. The correlation coefficients between
the seismic traces and the synthetic seismograms for the other wells are shown in the upper right corner for each of the wells in Appendix 3.A. The correlation coefficient in only the ZOI is shown in the lower right corner for each of the wells. The overall correlation coefficient in the ZOI for all of the wells was 69.63%. Figure 2.15 shows the amplitude spectrum of the seismic trace for Well A15 (top), the amplitude spectrum of the reflectivity (middle), and a comparison of the amplitude spectrum between the seismic trace and the synthetic (bottom); the comparison shows a reasonable match. The amplitude spectrum result for the other wells is shown in Appendix 3.B.

Figure 3.14  A comparison between the seismic trace and the synthetic seismogram at Well A15. The correlation coefficient from 700 ms to 1000 ms is 68%. The correlation coefficient in the ZOI (44 ms below the reservoir-top pick) is 79%.
Figure 3.15 A comparison of the amplitude spectra between the seismic trace and the synthetic seismogram for Well A15. The amplitude spectrum of the seismic trace at Well A15, and the amplitude spectrum of the reflectivity at Well A15 are shown in the upper and middle panels. The last panel is showing the comparison of the amplitude spectrum between the seismic trace (solid line) and the synthetics (dotted line).

3.6 CONCLUSIONS

3-D seismic data provide valuable information for 3-D reservoir modeling and characterization only if calibrated with geological data at the well locations.
Seismic attribute analysis and calibration are important tools for reservoir characterization. Edited sonic and density logs were used for creating the synthetic seismograms. First, the impedance and reflectivity logs were calculated at the well locations. Then, a wavelet was estimated. Note that an accurate estimate of the seismic wavelet can only be made after careful attention to the edited log data, which can affect the wavelet form and phase.

Next, the reflectivity logs were convolved with the wavelet to generate the synthetic seismograms. The overall correlation coefficient between the seismic traces at the well locations and their respectively generated synthetics was 70%.

In summary, calibration is important to minimize the errors caused by reservoir heterogeneities; however, it cannot supply all the answers needed for a quantitative spatial reservoir description. Nevertheless, the 3-D modeling inaccuracies caused by inter-well heterogeneities are considerably reduced.
CHAPTER 4   AN IMPROVED ESTIMATION OF THE RESERVOIR POROSITY USING MULTIPLE LINEAR REGRESSION

“Simplicity is the ultimate sophistication”

(Leonardo da Vinci)

This chapter utilizes the available data (the 3-D seismic data constrained by well logs) to estimate the porosity of the target carbonate reservoir in the study area using multiple regression method. Multiple (rather than just one) seismic attributes are used, and are supported by data clustering analysis to improve the accuracy of porosity estimates. An improved implementation of the multiple regression method that utilises cluster analysis output is proposed for obtaining more accurate estimate.

The clustering analysis indicates that the zone of interest (ZOI) is heterogeneous and can be subdivided horizontally into three distinct and contrasting subzones (3, 2, and 1; in a depositional sequence order), where linear regression can be employed within each subzone to predict porosity. Analyzing the reservoir by clustering analysis substantially improves the accuracy of the multiple regression method in estimating the porosity, here yielding a 45% improvement. Regional spatial mapping of the porosity indicates that the middle zone (Zone 2) has the best porosity, in terms of hydrocarbon exploration, within the limits of the reservoir. Next, the reservoir porosity maps at each level are interpreted for carbonate facies based on understanding the link between the carbonate depositional system and the inferred model of porosity in the area. The lithology is interpreted as shale-abundant, lime-dolomite-abundant, and anhydrite-abundant for the lower,
middle and upper subzones, respectively. Lithology, and hydrocarbon-saturation prediction of the ZOI were also obtained by mapping some important elastic properties; mainly, Vp/Vs and Poisson ratio for lithology and fluid-saturation indication, respectively. Other reservoir properties (velocity and density) were estimated from the modelled porosity.
4.1 INTRODUCTION

Point-by-point links between reservoir properties and their elastic responses have been successfully established by studies of rock physics. However, it is difficult to find a unique relationship between reservoir properties and seismic response. This non-uniqueness can be caused by different factors, such as the fact that conventional rock physics does not apply at the seismic scale, the limited resolution of the seismic waves, and the subsurface complexity and heterogeneity. The heterogeneity arises from the non-uniform, non-linear spatial distribution of rock properties. In the petroleum industry, it is important to understand the spatial distribution of the reservoir during its evaluation. Accurate prediction and mapping of the reservoir properties plays a key role in the successful description and analysis of the reservoir, and leads to a better quality subsurface geological model. Porosity, lithology, and permeability are considered the most important key properties in describing and characterizing the reservoir. Predicting reservoir properties such as porosity and lithology is one of the main goals of seismic data attributes analysis. Of these properties, porosity is the primary quantity used to construct a reliable reservoir model and evaluate the reservoir potential (Abhijit, 2006).

Porosity is a measure of the void space within a rock. It can be classified into two categories: effective or absolute porosity (Figure 4.1). Effective porosity is the interconnected void space and is related to permeability, whereas the absolute is the total porosity of the rock regardless of connectivity between the voids (Bradley, 1992). Generally, porosity decreases with increasing depth of burial. The range of porosity in petroleum reservoirs ranges from 5% to 45%, but it falls mostly between 10% and 20% (Jordine and Wishart, 1982). Porosity is one of the fundamental parameters for reservoir characterization and hydrocarbon volumetric determination. Accurate estimation of porosity
minimises risk and cost in exploration and development fields (Rapoport et al, 1997; Foster et al, 1993; Kalkomey, 1997). In most cases, lateral variations of porosity cannot be estimated from measurements made at sparsely located wells. The integration of 3-D seismic data and petrophysical measurements can significantly improve the spatial description of porosity by providing a dense and regular areal sampling of the reservoir properties.

The main objective of this chapter is to estimate the effective porosity of a carbonate reservoir using an improved implementation of the multiple linear regression approach, whereby cluster analysis is applied before multiple regression analysis so that the output of the clustering analysis can improve the performance of the multiple regression method. This improved implementation is demonstrated to generate a more accurate porosity estimate than conventional methods.

The workflow is as follows: first, to check the resulting output of the pre-analysis stage and prepare the main input attributes for the analysis. Second, is to run a hierarchical clustering analysis. Third, is to compare the prediction results between the conventional multiple linear regression method and the proposed method that utilizes the clustering output in the analysis. Fourth, the result is blind-tested for validation. Next, 2-D porosity maps are generated then used to map other reservoir properties and elastic moduli (constants). Finally, lithology and fluid saturation are inferred for the different subzones.

The remainder of this chapter is divided into six sections. Section 4.2 briefly describes the multiple regression method and emphasizes the importance of this technique for reservoir characterization studies, before listing examples of some previous applications of multiple regression and finally highlighting the differences between these previous studies and the approach suggested here.
Section 4.3 introduces cluster analysis, which is used to improve the multiple regression. Section 4.4 presents the results, which are interpreted in Sections 4.5 and 4.6. Finally, conclusions are drawn in Section 4.7.

**Figure 4.1** The effective porosity and the absolute porosity. The permeable spaces and the void spaces contribute to effective porosity and absolute porosity, respectively.

### 4.2 METHOD

Multiple linear regression coupled with other approaches (such as geostatistical) has being explored as a tool for correlating well logs and seismic data, as well as, for mapping the distribution of reservoir properties within 3-D seismic image volumes (Hart et al., 2000). Multiple linear regression is one of the most popular methods for combining seismic attributes, especially for carbonate reservoirs. Multiple regression is an extension of univariate regression analysis that incorporates additional independent variables in the
predictive equation, and is accordingly classed as a polynomial curve fitting and trend surface analysis technique (Davis, 2002). Just as trend surfaces extend curve-fitting procedures to two-dimensional space, multiple regression is a further extension of linear regression to multi-dimensional space. Several case histories reported in the literature have used multiple regression to predict the reservoir properties. For example, Schuelke and Rick (2003) and Calderon and Castagna (2007) have suggested using multiple seismic attributes to estimate log properties; Russell et al. (1997) used a linearly weighted sum over different attributes to estimate the distribution of a reservoir property; and Schuelke and Quirein (1998), Hampson et al. (2001) and Pramanik et al. (2004) suggested a technique to select seismic attributes and to verify their results.

The approach in this chapter is similar to that employed by Hampson et al. (2001); however, the difference is that the multiple regression equation is allowed to vary with stratigraphy, which is pre-defined by hierarchical clustering, to improve the accuracy of the regression. The general model is:

\[ P = w_0 + w_1 A_1 + \ldots + w_m A_m \]  \hspace{1cm} (4.1)

where \( W_i \), \( i = 0, \ldots, m \) are the \( m+1 \) weights, \( P \) is the property to be estimated (porosity), and \( A_m \) are the \( m \) seismic attributes.

Any observed variable can be considered to be a function of other variables measured on the same sample level. In multiple regression problems, the interest is usually in the relative effectiveness of the independent variables as predictors of the dependent variable. In addition, regression provides the best estimate of the mean (Deveton, 1994). The ability of a regression model to predict is enhanced through the weighting scheme.

A least-squares solution to a linear equation of this type can also be found by solving a set of normal equations for the weighting coefficients \( w_i \). This method has numerous advantages over conventional inversion procedures: (1) it can transform the seismic cube into any well log property, and (2) it uses cross-
validation as a measure of success (Hampson et al., 2001).

4.3 CLUSTER ANALYSIS

Cluster analysis, also called ‘segmentation analysis’ or ‘taxonomy analysis’, seeks to identify a set of groups which both minimize within-group variation and maximize between-group variation (Backer, 1995). In other words, cluster analysis is an **exploratory data analysis** (EDA) tool which aims at sorting different objects into groups in such a way that the degree of association between two objects is maximal if they belong to the same group and minimal otherwise (Aldenderfer, 1993). One of the main objectives of clustering is to reduce the amount of data by grouping similar data items together. One of the motivations for using clustering algorithms is to provide tools for constructing categories or taxonomies (Jardine and Sibson, 1971; Sneath and Sokal, 1973). In general, clustering methods can be divided into two main kinds: partitional and hierarchical clustering. Different subtypes and algorithms exist within each of these two types.

Partitional clustering, attempts to directly decompose the data set into a set of disjoint groups. The local structure of the data may be emphasized through the criterion function that the clustering algorithm tries to minimize, by assigning clusters to peaks in the probability density function, or the global structure. Typically the global criteria involve maximizing the dissimilarity of different clusters, while minimizing some measure of dissimilarity in the samples within each cluster.

Hierarchical clustering, on the other hand, proceeds successively by splitting large clusters, or merging smaller clusters into larger ones. The clustering
methods differ in the rule by which it is decided which two small clusters are merged or which large cluster is split. The dendrogram is the end result of the algorithm which represents a tree of clusters showing how the clusters are related.

Therefore, cluster analysis can be used to discover structures in the data without providing any explanation, interpretation or reasoning. Tree clustering is one type of clustering analysis (Gelman and Hill, 2007), which joins objects (e.g., time samples) together into successively smaller clusters, using some measure of similarity or distance. The most straightforward and intuitive way of computing distances between objects in a multi-dimensional space is the Euclidean distance, which is simply the geometric distance (the shortest distance) between the two points in multidimensional space.

Therefore, the data were analysed in more detail to enable better assessment of whether any relationships do indeed exist. This was achieved using cluster analysis, which can assess whether the heterogeneity of the reservoir is the driving cause of observed variations in the attributes. The cluster analysis indicates that the zone of interest (ZOI) can be divided into three separate sub-zones (Figure 4.2). Figure 4.3 shows cross-plots result of the porosity against each of the four attributes, for each zone individually, at Well A15. These relationships are clearer than those obtained when the whole ZOI was used. The goodness of fit in the cross plots was measured by the correlation coefficient between the observed and the predicted property values (Draper and Smith, 1966).
Figure 4.2 The result of the clustering analysis within the ZOI. There are three broad clusters for the 12 time slices: the first clustering group comprises time slices 924 ms to 932 ms; the second group comprises slices 936 ms to 948 ms; and the third group comprises time slices 952 ms to 968 ms.
Figure 4.3 The cross-plot of porosity with each of the four attributes within the different subzones at Well A15 is shown in four panels: (a) porosity vs. instantaneous amplitude, (b) porosity vs. instantaneous phase, (c) porosity vs. instantaneous frequency, and (d) porosity vs. acoustic impedance. The three main subzones of the zone of interest are shown in each panel.
4.4 IMPROVEMENT AND VALIDATION

A linear relationship between porosity and seismic attributes may not be clear, due to the complexity and heterogeneity of the carbonate reservoir. However, with thrift analysis prior to the regression analysis, cluster analysis indicates that the ZOI is divided into three subzones, which (in depositional order) are the lower subzone from 952 to 968 ms, middle subzone from 936 to 948 ms and upper subzone from 924 to 932 ms (Subzones 3, 2 and 1, respectively). This finding gives a noticeable difference in the prediction accuracy. Figure 4.4 compares the improved multiple linear regression method (suggested in this paper) and the conventional multiple linear regression method for predicting the porosity. Regression over the whole reservoir section yields an overall correlation coefficient of 54.6% (the left side of Figure 4.4), whereas a noticeable enhancement in the model prediction is achieved when applying the method separately to each subzone, as suggested here (the right side of Figure 4.4); the overall correlation coefficient in this case is 79%. One way of validating the result is to remove a random well from the calculation and check the porosity prediction at that well (Schuelke and Quirein, 1998). The primary goal is to blindly test the model’s capability of estimating the porosity for any location without using that location’s data in the model calculation. The ‘take-one-out’ method, alternatively known as a ‘Jack-knife’ method is a form of a bootstrap technique which is an effective way of graphically estimating the magnitude of error (Efron, 1993; Shao, 1995). Figure 4.5(a) shows the validation result when one well (A03) is removed. When a significant number of wells (A03, A18, and A20) are removed out from the calculation, the model loses its power to predict the porosity (Figure 4.5 (b)).
Figure 4.4 The improvement in porosity prediction within the ZOI. For each well, the correlation coefficient values between (the data and the model), and (the data and the improved model) are shown in the upper-right corner, and lower-right corner of the well panel, respectively. The overall correlation coefficient between the actual (solid black curve) and predicted (dotted black curve) porosity for all wells is 54.6%. The prediction was improved by calculating the regression equation for the three subzones (zone1, zone2, and zone3) separately, increasing the overall correlation coefficient to 79% (solid blue curve).
Figure 4.5  Validating the prediction result of the improved model at the eight well locations: (a) one random well (A03) is removed from the calculation, and (b) a significant number of wells (A03, A18, and A20) are removed. The prediction accuracy deteriorates as more wells are taken away from the calculation.
4.5 INTERPRETATION

The 2-D porosity regional mapping generated from the improved multiple linear regression is presented in Figure 4.6, and clearly shows the lateral variations in porosity within the three individual time horizon-slices from 924 to 968 ms. The fourth slice (slice 936 ms) reflects higher porosity values, over most of the study area, than the other slices, and is therefore considered as the main production target of the reservoir. The five slices at the bottom of the ZOI (slices 952 ms to 968 ms; Subzone 3) show medium porosity values (from 6% to 16%), the middle four slices (slices 936 ms to 948 ms; Subzone 2) have the highest porosity values (ranging between 10% and 36%), and the upper three slices (slices 924 ms, 928 ms and 932 ms; Subzone 1) have the lowest porosity values, which are less than 11%. The average porosities for each slice ranged from 9-13%, 18-27% and 2-7% for the lower, middle and upper subzones, respectively (Figure 4.7).

In the following step, porosity is linked to the carbonate facies model by building a 1-D porosity model that captures the general porosity pattern (Figure 4.7). This is used to interpret the regional maps of the three subzones. Subzone 3 is interpreted as a deep marine environment, with low energy deposits that occur in the outer ramp (the right image of Figure 4.10). Grainstone and packstone reservoirs, for example, are common in ramp settings and can occur in a number of variations (Schuelke and Rick, 2003). According to the carbonate depositional system model (Figure 2.3), this facies is interpreted as lime mudstone, because mud dominates the deep ramp deposits and usually forms thick beds through constructing a 1-D model (Figure 4.8). Rudstone is usually deposited at intermediate depth level on the ramp (Fontaine et al, 1987). Therefore, these slices represent a combination of deep-moderate ramp
deposits, mainly comprising mudstone, rudstone and wackestone.

The high range of porosity values of slices in Subzone 2 suggests sedimentation was interrupted. Subzone 2 is interpreted as the carbonate facies deposited on the shelf (lower shoreface). The carbonate sand bodies and shoals are some of the major facies deposited in a shoreline setting. The first slice in Subzone 2 clearly stands out as the most porous zone in the reservoir; therefore, it is interpreted as the major facies of the intrashelf deposits, which comprise corals deposited as sheets (the middle image of Figure 4.9) (Jordine and Wishart, 1982). This slice is interpreted to be the main production layer in the reservoir.

Packstone, intra-clastic rudstone and grainstone are common lithofacies of the grain-dominated facies (Subzone 1), while lime mudstone, wackestone, grainshoal and coral are common lithofacies in the mud-dominated and organic-dominated facies (Subzones 2 and 3) (Moore and Jones, 1985). Grainstone, packstone, and grain shoal are high-energy deposits that occur in a shallow depositional environment. The first slice in Subzone 1 shows the lowest porosity and can be represented by evaporites; this slice is interpreted to be the sealing layer (the left image of Figure 4.9).
Figure 4.6 The top-view spatial distribution of the estimated porosity at each of the individual horizon slices within the ZOI. The fourth horizon slice (slice 936 ms) has the highest porosity values over most of the study area. The first
three slices (Subzone 1) show the lowest porosity values (less than 11%); the following four slices (Subzone 2) have the highest porosity values (10-36%); while the last five slices (Subzone 3) have moderate porosity values (6-16%). These three groups correspond to three distinct subzones of the reservoir: upper, middle and lower.
Figure 4.7 The regional distribution of the average porosity for each of the three individual Subzones. The average porosity ranges from 2-7%, 18-27% and 9-13% for Subzones 1 (upper), 2 (middle) and 3 (lower), respectively. The eight well locations are annotated in the figure.
Figure 4.8 A 1-D model capturing the general porosity pattern at the well locations. Packstone, intra-clastic rudstone and grain-stone are common lithofacies in the grain-dominant deposits (Subzone 1), while lime mudstone, wackestone, grainshoal and coral are common lithofacies in mud-dominant and organic-dominant facies (Subzones 2 and 3).
**Figure 4.9** The interpretation of Subzones 1, 2 and 3. Subzone 1 shows the lowest porosity values; it is interpreted as an evaporite sealing layer.
Grainstone, packstone and shoal are high-energy deposits that occur in a shallow depositional environment. Subzone 2 is interpreted as the carbonate facies deposited on the shelf, because of the high porosity values that suggest sedimentation interruption. The first slice in this zone (936 ms in Figure 4.6) is the main contributor to the high porosity values; it is interpreted as a coral facies of the intra-shelf region, deposited as sheets. Subzone 2 is considered as the main production zone of the reservoir. Subzone 3 represents the deep marine environment with low energy deposits that occur in the outer ramp. The interpretation is based on the dominant mudstone and wackestone facies, which are common facies in ramps.

4.6 USING POROSITY TO ESTIMATE RESERVOIR PROPERTIES

The modelled reservoir porosity is next used to estimate the spatial distribution of some of the important reservoir properties, such as compression and shear wave velocities ($V_p$, $V_s$) and density. These reservoir properties are then used to predict the distribution of elastic moduli such as the bulk modulus, shear modulus, Young’s modulus, Lame’s constant ($V_p/V_s$ ratio) and Poisson ratio. The elastic parameters are useful for characterising the reservoir’s lithology and fluid content. Typical physical properties of dolomite and limestone were published by Mavko et al. (1998) and are listed below in Table 4.1.
Dr. ALMOQBEL, A.
Sep 14, 2011

<table>
<thead>
<tr>
<th>Physical Property</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dolomite</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Vp (km/s)</td>
<td>3.41</td>
<td>7.02</td>
<td>5.39</td>
<td>0.69</td>
</tr>
<tr>
<td>Vs (km/s)</td>
<td>2.01</td>
<td>3.64</td>
<td>2.97</td>
<td>0.37</td>
</tr>
<tr>
<td>Vp/Vs</td>
<td>1.59</td>
<td>2.09</td>
<td>1.82</td>
<td>0.07</td>
</tr>
<tr>
<td>Porosity</td>
<td>0</td>
<td>0.32</td>
<td>0.13</td>
<td>0.06</td>
</tr>
<tr>
<td>Density (g/cm(^3))</td>
<td>2.27</td>
<td>2.84</td>
<td>2.59</td>
<td>0.12</td>
</tr>
<tr>
<td>Impedance 10(^7) (kg/m(^3) m/s)</td>
<td>0.78</td>
<td>1.93</td>
<td>1.4</td>
<td>0.23</td>
</tr>
<tr>
<td><strong>Limestone</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Vp (km/s)</td>
<td>3.39</td>
<td>5.79</td>
<td>4.63</td>
<td>0.66</td>
</tr>
<tr>
<td>Vs (km/s)</td>
<td>1.67</td>
<td>3.04</td>
<td>2.44</td>
<td>0.37</td>
</tr>
<tr>
<td>Vp/Vs</td>
<td>1.72</td>
<td>2.04</td>
<td>1.88</td>
<td>0.08</td>
</tr>
<tr>
<td>Porosity</td>
<td>0.03</td>
<td>0.41</td>
<td>0.15</td>
<td>0.09</td>
</tr>
<tr>
<td>Density (g/cm(^3))</td>
<td>2</td>
<td>2.65</td>
<td>2.43</td>
<td>0.16</td>
</tr>
<tr>
<td>Impedance 10(^7) (kg/m(^3) m/s)</td>
<td>0.69</td>
<td>1.51</td>
<td>1.43</td>
<td>0.22</td>
</tr>
</tbody>
</table>

Table 4.1 Typical physical properties of dolomite (top) and limestone (bottom) (Mavko et al., 1998). The five columns represents (from left to right): the physical property, the minimum value, the maximum value, the average value, and the standard deviation.

4.6.1 Density and V\(_p\)

Density and V\(_p\) can be estimated empirically, for example by using Gardner’s formula (Gardner et al., 1974), or by multiple regression analysis. Rafavich et al. (1984) performed detailed laboratory experiments to study the relationship between velocity and petrographic characteristics in carbonates. Their work indicated that P-wave (V\(_p\)) and S-wave (V\(_s\)) are primarily influenced by rock porosity and rock density. Gardner’s formula is:

\[
\text{Density} = a \cdot V_p^f \hspace{1cm} \text{……………….. (4.2)}
\]

where \(a\) and \(f\) are Gardner’s constants. The parameters \(a\) and \(p\) are lithology dependent (Table 4.2). Estimates of density made using regression are compared with those of other methods in Figure 4.10.
Table 4.2  Gardner’s constants (‘a’ and ‘f’) for different lithologies (sandstone/shale, limestone, and dolomite).

<table>
<thead>
<tr>
<th>Lithology</th>
<th>a</th>
<th>f</th>
</tr>
</thead>
<tbody>
<tr>
<td>SS/Sh</td>
<td>1.741</td>
<td>0.250</td>
</tr>
<tr>
<td>Limestone</td>
<td>1.500</td>
<td>0.225</td>
</tr>
<tr>
<td>Dolomite</td>
<td>1.740</td>
<td>0.252</td>
</tr>
</tbody>
</table>

Figure 4.10  A comparison between the regression and empirical methods for predicting density. The result shows better correlation between the data (solid red curve) and the regression model (solid blue curve) than the correlation between the data and other empirical models.
4.6.2 Shear Velocity ($V_s$)

Two of the wells have $V_s$ logs: A20 and A21. The regression method was also used to predict the shear velocity from the p-wave velocity. Figure 4.11 shows a comparison between the regression method and other methods for estimating the shear velocity, and illustrates that the regression method generates more accurate estimates (with a higher correlation coefficient) than the other methods. The 2-D mapping results of the regression mapping are included in Appendices 4.A, 4.B, and 4.C for $V_p$, $V_s$ and density, respectively.
Figure 4.11 A comparison of different Vs profiles (regression vs. empirical) with the actual log for Wells A20 (left panel) and A21 (right panel).

4.6.3 Elastic Parameters

$V_p$, $V_s$ and density are needed for estimates of common elastic parameters, as follows:

1) Poisson’s ratio

$$\sigma = \frac{0.5(V_p/V_s)^2 - 1}{(V_p/V_s)^2 - 1} = \frac{E - 2\mu}{2\mu} \quad \text{……………… (4.3)}$$

2) Bulk modulus

$$k = \frac{E}{3(1-2\sigma)} \quad \text{……………… (4.4)}$$

3) Rigidity modulus

$$\mu = \rho V_s^2 \quad \text{……………… (4.5)}$$
4) Young modulus  \[ E = \rho V_s^2 \frac{(3V_p^2 - 4V_s^2)}{(V_p^2 - V_s^2)} \], and \[ \ldots \ldots \ldots (4.6) \]

5) Lame’s constant  \[ \lambda = k - \frac{2\mu}{3} \], \[ \ldots \ldots \ldots (4.7) \]

Estimates of both \( V_p \) and \( V_s \) can therefore be very useful in mapping reservoir lithology, elastic properties and fluid distribution. For example, lithology was modelled in Section (4.5) based on geological and depositional information, but can also be predicted through the use of elastic parameters based on geophysical information. Mapping the Poisson and \( V_p/V_s \) ratios yields a regional distribution of the reservoir properties (fluid-saturation and lithology).

\[ 4.6.3.1 \text{ Compression wave velocity / Shear wave velocity ratio (} V_p/V_s \text{)} \]

One useful lithology indicator is the \( V_p/V_s \) ratio. Extensive laboratory research suggests that shear-wave data analysed in conjunction with compression-wave data can provide additional information on rock properties. Nations (1974), Kithas (1976), and Miller and Stewart (1990) all concluded in their log studies that there is a correlation between lithology and \( V_p/V_s \) ratio. Pickett (1963) established \( V_p/V_s \) values from cores for different lithologies (Table 4.3). It was also found that even a small hydrocarbon (HC) saturation noticeably decreases \( V_p \) and increases \( V_s \) in porous rocks.
Table 4.3  Pickett’s $V_p/V_s$ values for different lithologies (from top to bottom): shale, limestone, dolomite, calcareous sandstone, and clean sandstone. This ratio is good indicator to lithology type.

<table>
<thead>
<tr>
<th>Lithology</th>
<th>$V_p/V_s$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shale</td>
<td>2.0-3.0</td>
</tr>
<tr>
<td>Limestone</td>
<td>1.90</td>
</tr>
<tr>
<td>Dolomite</td>
<td>1.80</td>
</tr>
<tr>
<td>Calcareous SS</td>
<td>1.70</td>
</tr>
<tr>
<td>Clean SS</td>
<td>1.60</td>
</tr>
</tbody>
</table>

After estimating the compression velocity ($V_p$) and shear velocity ($V_s$) through the proposed improved regression method, the regional reservoir lithology distribution is mapped then interpreted using the $V_p/V_s$ ratio. A drop in $V_p/V_s$ may be due to an increase in porosity, a decrease in shaliness, a change in pore fluid content, or some combination of more than one of these factors. A wider $V_p/V_s$ range within a local area indicates lithological heterogeneity. Results for a cross-section in the study area are shown in Figure (4.12). The horizon-slice mapping for Subzone 1, Subzone 2, and Subzone 3 are shown in Figure (4.13). Appendix 4.D shows the $V_p/V_s$ 2-D mapping for the individual horizon slices within the ZOI.
Figure 4.12  Vp/Vs mapping through Well A15, as shown by two blue cross-sections. (a) is a map view of the study area showing the cross sections, (b) is the Vp/Vs mapping in the inline direction through Well A15, and (c) is the Vp/Vs mapping crossline direction through Well A15.
Figure 4.13  Mean Vp/Vs horizon-slice mapping of the three Subzones (from top to bottom): 1(upper), 2 (middle), and 3 (lower).
4.6.3.2 Poisson ratio (σ)

The Poisson ratio, which depends on the $V_p/V_s$ ratio, provides tighter constraints on lithology than either the compression or shear velocity alone. Poisson ratio is an elastic constant that is a measure of the compressibility of material perpendicular to the direction of applied stress; or the ratio of the compression strain (normal to the applied load) to the extension strain (in the direction of the applied load (Abhijit, 2006). Stiffer materials have a lower Poisson ratio than softer materials. For example, sandstone (stiff) has a Poisson ratio in the order of 0.2, while carbonate rocks (soft) have a Poisson ratio in the order of 0.3; Poisson’s ratio is therefore useful in predicting the distribution of pore fluids. Table 4.4 lists values of the Poisson ratio in different media.

<table>
<thead>
<tr>
<th>Lithology &amp; Fluid</th>
<th>Poisson</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sandstone (SS)</td>
<td>0.15-0.33</td>
</tr>
<tr>
<td>Porous gas SS</td>
<td>~0.10</td>
</tr>
<tr>
<td>Porous oil SS</td>
<td>~0.25</td>
</tr>
<tr>
<td>Shale</td>
<td>0.25-0.35</td>
</tr>
<tr>
<td>Clean SS</td>
<td>0.30-0.40</td>
</tr>
</tbody>
</table>

Table 4.4 Poisson ratio for different saturated and non-saturated lithology types (Simmons and Wang, 1971); from top to bottom: sandstone, porous gas sandstone, porous oil sandstone, shale, and clean sandstone.
Figure 4.14 shows the result of mapping the Poisson ratio through the two cross-sections passing through Well A15. The average Poisson ratio has been mapped for the three subzones: Subzone 1, Subzone 2 and Subzone3 (Figure 4.15). The 2-D mapping of Poisson ratio for the individual horizon slices within the ZOI is included in Appendix 4.E.
Figure 4.14 Poisson ratio mapping through Well A15, as shown by two blue cross-sections. (a) is a map view of the study area showing the cross sections, (b) is the Poisson ratio mapping in the inline direction through Well A15, and (c) is the Poisson ratio mapping crossline direction through Well A15.
Figure 4.15  Mean Poisson ratio horizon-slice mapping of the three Subzones (from top to bottom): 1(upper), 2 (middle), and 3 (lower).
4.7 CONCLUSIONS

In this chapter, regional mapping of porosity (one of the important reservoir properties) was predicted using an improved analysis technique that combined multiple linear regression with clustering analysis. The clustering analysis result therefore provided valuable information on the heterogeneity of the carbonate reservoir, leading to the improved accuracy of the regression analysis. The clustering analysis result in this chapter has indicated that the ZOI is best divided into three subzones, where each individual subzone showed a better linear relationship between each of the input seismic attributes (instantaneous amplitude, instantaneous phase, instantaneous frequency and acoustic impedance) and porosity than that for the ZOI as a whole. The improved implementation of the approach led to an increase in the prediction accuracy of the porosity; the overall correlation coefficient has increased from 56 % to 79 %.

The porosity volume has been generated, and then used to regionally predict other reservoir properties such as p-wave and density by making use of the well logs and using the improved MLR technique described in this chapter. The spatial distribution of the s-wave velocity was also estimated utilizing the observed linear relationship between the p-wave velocity and the s-wave velocity at well locations. Having both volumes (p-wave velocity and s-wave velocity) in hand, some useful elastic modulus have revealed important lithological and fluid information. The lithological information has coincide with the facies interpretations that were drawn based on the spatial distribution of the reservoir porosity and knowledge of the link between carbonate depositional setting and the general pattern of the porosity in the study area.
In sum, the improved implementation of this chapter methodology has generated reasonable estimation of the porosity as was proved from the validation process. The proposed implementation has boosted the estimation accuracy by 45% over the conventional approach. The analysis has also indicated that the most porous subzone of the ZOI is the middle one (subzone 2) which concluded to be dominated by limestone and dolomite. Anhydrite and mud have been interpreted/expected to dominate the lithology of subzones 1 and 3, respectively.
CHAPTER 5  CARBONATE RESERVOIR CHARACTERIZATION BASED ON GREY SYSTEM THEORY

“When a distinguished but elderly scientist states that something is possible, he is almost certainly right. When he states that something is impossible, he is very probably wrong”
(Sir Arthur C. Clark)

In this chapter, I introduce grey system theory (GST) to highlight the anomalous zones of the carbonate reservoir under investigation. This GST approach analyzes the internal structure of the data without the need to include external elements. The dynamic setting of the equations accentuates the difference between the data and the calculated background value. This difference is proposed and used as an indicator for hydrocarbon-bearing zones. Results show that the proposed hydrocarbon-indicator (HI) is closely related to the distribution of the hydrocarbon-bearing reservoir, and yields a good correlation with the wells production classification. Therefore, it is considered as a new promising HI tool for highlighting reservoir hydrocarbons.
5.1 INTRODUCTION

Identifying reservoir hydrocarbon-bearing zones is a fundamental challenge facing reservoir geophysicists. Conventional approaches such as artificial neural networks and pattern recognition may not perform well for a heterogeneous carbonate reservoir, thus posing real exploration challenges in predicting favourable zones. These techniques require additional information, such as well logs, core data, or a geological model, in order to perform adequately. For a carbonate reservoir, the heterogeneous nature of the reservoir adds complexity that can impair the accuracy of the results. A new method which uses a more limited number of input data and which produces output with more recognizable hidden feature is therefore desirable.

Grey system theory (GST) is a method devised for uncertain situations, and offers a framework in which to investigate a new discipline within the oil and gas industry. One of the advantages of the grey method is its ability to deal with noisy data sets, making it an ideal tool for investigating the complex carbonate reservoir of the study area. The grey method is also particularly suited for analyzing systems with poor, incomplete or uncertain data (Xie et al., 2009; Lim et al., 2008).

The term ‘grey system’ was chosen based on the colors of the subject under investigation. For example, in control theory, the description of color has been commonly used to indicate the degree of clarity of information. In system control theory, a white system is “a system for which the relevant information of the system is known completely”, while a system for which “the relevant information is completely unknown” is called a black system (Lu and Wevers, 2007; Lin, and Liu, 2004). The grey system is a system that falls between these
two systems, and is therefore defined as being “a system with partially known and partially unknown information” (Figure 5.1).

![Diagram](image)

**Figure 5.1** A ‘grey system’ is a system that falls between the white system and the black system. It is a system with partially known and partially unknown information.

Grey prediction is one of the most important aspects of GST. Grey prediction develops the known information; the missing information (valuable information) is then usually extracted from the partially known information (Fan et al., 2003). In other words, the grey prediction brings the grey system closer to the white system by utilizing the current known knowledge about the system.

Like many research fields, reservoir characterization research activities face situations with incomplete/missing information. Hence, a reservoir is a grey system because part of the information is known, and GST is therefore used in the grey modeling to reveal some of the missing information. The reservoir
physical parameters are usually unknown or partially known, so the reservoir is a system with grey properties (Cai, 1993; Wu et al., 2005; Wong, 2006). A key operation in the construction of a grey model is the use of discrete time sequence data to build up an ordinary differential equation (Wu et al., 2005; Chang et al., 2004).

The grey model is summarized by the following five steps:

1) Given the original data set

\[ X^0 = [x^0(1), x^0(2), \ldots, x^0(n)], \ldots \] \hspace{1cm} (5.1)

where \( x^0(i) \) corresponds to the system output at time \( i \),

2) A new sequence is generated:

\[ X^l = [x^l(1), x^l(2), \ldots, x^l(n)], \ldots \] \hspace{1cm} (5.2)

where

\[ x^l(k) = \sum_{m=1}^{k} x^0(m), \ldots \] \hspace{1cm} (5.3)

3) Form the first-order differential equation

\[ \frac{dx^l(k)}{dk} + ax^l(k) = u, \ldots \] \hspace{1cm} (5.4)

4) Obtain \( a \) and \( u \)

\[ \begin{bmatrix} a \\ u \end{bmatrix} = (B^T B)^{-1} B^T y_N, \ldots \] \hspace{1cm} (5.5)
where

$$B = \begin{bmatrix}
-\frac{1}{2}(x^1(1) + x^1(2)) & \cdots & 1 \\
-\frac{1}{2}(x^1(2) + x^1(3)) & \cdots & 1 \\
\vdots & & \vdots \\
-\frac{1}{2}(x^1(n-1) + x^1(n)) & \cdots & 1
\end{bmatrix}, \text{ and } \ldots \ldots \ldots \ (5.6)$$

$$y_N = [x^0(2), x^0(3), \ldots, x^0(n)]^T. \ldots \ldots \ldots \ldots \ (5.7)$$

5) The predictive function is

$$\tilde{x}^0(k) = (x^1(1) - \frac{u}{a})e^{-uk} + \frac{u}{a}, \ldots \ldots \ldots \ldots \ (5.8)$$

and the predicted value at time $k + 1$ is

$$\tilde{x}^0(k + 1) = \tilde{x}^0(k + 1) - \tilde{x}^0(k), \ldots \ldots \ldots \ldots \ (5.9)$$

The method suggests that samples of a seismic trace are not isolated; therefore, a relationship between adjacent-samples can exist. This relationship between seismic data samples is referred to as ‘a seismic data structure’ and is utilized in this study for identifying the reservoir hydrocarbon accumulations.

The proposed attribute for classification is defined as the relative error between the data value and the model’s calculated value (background). After finding good correlation between the proposed attribute values and the wells production classification, this attribute is proposed as an indicator of HC-bearing zones. The method remedies the deficiencies of traditional prediction methods by closely focusing on extreme values.
5.2 GREY METHOD FOR HYDROCARBON INDICATION

The input data comprise a 3-D seismic cube along with eight wells drilled in the study area. The wells have varying production quality; five, two and one of the wells are low, moderate, and high production wells, respectively. The basemap shows the aerial range of the study area, along with the eight wells with their production classification (Figure 5.2).
Figure 5.2 A basemap showing the study area coverage and the wells production classification. There are five low-non producing wells, two moderate producing wells, and one highly producing well. The x axis and y axis are the distance in kilometres.

After calibrating the data and selecting the ZOI at 44 ms below the top-reservoir pick, from 924 to 968 ms, the grey model was built and the analysis was run. Amplitude signatures at hydrocarbon-bearing interfaces show different characteristics to those of non-hydrocarbon-bearing interfaces.
Therefore, analyzing the amplitude characteristic of seismic reflection waves using GST helps to capture hydrocarbon signatures. The grey model is based on a single series model, so is not affected by the surrounding factors, therefore leading to more recognizable feature in the model. The method analyses the internal structure of the seismic data on a trace-by-trace basis. The analysis is performed in a continuous dynamic process by defining a set of relationships as differential equations in the grey domain. The approach in this chapter is characterized by better differentiation of waveforms than in other conventional approaches where amplitude characteristics are stacked on each other to form a strong amplitude anomaly, which cannot clearly show changes to the waveform.

The grey value in the GST is utilized to detect irregularities (HC-indicators) in the proposed seismic data structure characteristics through a data generation technique, which is an important step in the theory of grey systems. The process generally includes two operations: an accumulated generation operation (AGO) and an inverse accumulated generation operation (IAGO). AGO and IAGO operations are used to find the grey differential model. First, the governing rule is captured by calculating the seismic trace absolute value to form a new processed trace. The new processed trace is then mapped into the grey domain by the accumulated generating operation (AGO). AGO is an iterative addition to the time series data which increases monotonically; it is considered as a whitening operation in the grey process (Shimizu, et al., 1998).

Irregularities in the internal structure of the data can be sensed through the integration step of the AGO that generates a smooth discrete function in an exponential form. This step regulates the input and generates smoother system-input behavior (with less randomness) for the analysis, as well as, exploring the governing laws in the system (Lin and Liu, 2004). Therefore, the main purpose
of AGO is to turn raw data (irregular) into a regular smooth series. A set of differential equations is set for the grey modeling after AGO data generation, then the parameters $a$ (the developing coefficient) and $u$ (the grey input) are solved by a least square algorithm. The method next transforms the independent discrete data into continuous predictable data by generating the grey values. This use of discrete time sequence data to build a set of continuous dynamic ordinary differential equations is a promising way of revealing the missing information, and is called the whitening of the model (Lin, 2007; Tien, 2005).

The parameters found in the previous steps are utilized to generate the grey model of the input data. IAGO transforms the AGO sequence data back to a raw data sequence. This step is performed after completing the grey prediction in the grey domain. The relative difference between the data values and the model values (internal structure values) is proposed as a measure of the missing information in the reservoir system; it is used as the attribute (grey hydrocarbon indicator) to highlight the productive reservoir zones. From the theoretical point of view, the model parameters ($a$ and $u$) are mainly influenced by non-HC reservoir reflection amplitudes. The prediction error of the grey model is mainly controlled by the quantity, which indicates the relative magnitude of changes in the reflection amplitude when working with non-HC reservoirs.

### 5.3 FIELD DATA APPLICATION

First, the grey model is applied to the 1-D amplitude traces at the eight well locations. Then, the 2-D model was run to map the grey hydrocarbon indicators at the different reservoir levels. The main 1-D grey modeling process
(workflow) is graphically shown for Well A15 in Figure 5.3. Starting with the original seismic trace, the method assumes positive data values for the grey trace. Then, it is transferred to the grey domain where different difference equations are built to predict the model. The comparison between the ‘data’ and ‘model’ traces is transferred back to the input domain where the proposed attribute is defined as the relative difference between the two curves. The grey anomaly values vary in the range of -5 to +5 (dimensionless units). The prediction of the model was improved by implementing the grey analysis in three distinct reservoir zones (instead of the whole ZOI), which were obtained from the cluster analysis. Figure 5.4 shows the results of the 1-D modeling at the eight well locations, and also the improvements in the model prediction achieved when using the combined zones. The results yield an overall correlation of 77%.

By analyzing the output values of the grey hydrocarbon indicator for the eight wells, two features are noticeable: (1) some samples have high indicator values (marked in red), as shown in Table 5.1, and (2) these high values occur more frequently at the 936 ms level, in six out of eight wells. The results of the analysis indicate that a high deviation from zero is a strong indicator of hydrocarbon presence. It can be seen from the grey anomaly values of the seismic traces at the well locations that the hydrocarbon-bearing interval (top of Zone 2) has higher grey attribute values.
Figure 5.3 The 1-D grey modelling process (workflow) for Well A15. It shows the main processing steps to obtain the proposed grey attribute for Well A15.
In order to validate the results, the grey attribute was mapped in 2-D to check the consistency of the available wells’ production classifications. The grey attribute was mapped for each of the different reservoir levels (Figure 5.5), revealing a consistent relationship between the grey attribute and the data production classification for most of the wells on the fourth horizon slice at time 936 ms. The proposed method utilizes the characteristics of the seismic data structure and shows how these can be correlated with hydrocarbon information. The fourth horizon slice (936 ms) yielded the highest consistency, demonstrating that the grey analysis can be used as a powerful tool in
characterizing the reservoir, especially in carbonate regions, for hydrocarbon accumulation. Results were smoothed by running a five-point moving average window to identify the more general trends in the area (Figure 5.6).
Figure 5.5  The 2-D mapping (map-view) of the grey attribute for the different horizon slices within the ZOI. The fourth horizon slice (at time 936 ms) shows distinctly larger extend of grey attribute values.
Figure 5.6 The grey attribute map of the fourth horizon slice at 936 ms (top). This result is then smoothed to show the general trends within the study area (bottom).
A key branch of GST is the grey incidence theory (GIT), also known as ‘grey relation analysis (GRA)’. The grey relation model accounts for impact measurements of a relationship that changes between systems, or between elements within the systems (Li, 2009). The impact measurement is also called ‘the grade of relation’, and is used to reveal correlation between the known and unknown information in the system assessed, as well as, for determining their incidence grade. This measurement lays the foundations of the classification analysis and is a tool that is useful in pattern recognition, clustering and decision-making processes (Hu et al., 2007). During system development, a higher grade of relation is considered to indicate that the covariance between two elements is low. Here, the method can determine the grade of the grey relationship based on the similarity between elements. The fundamental idea is that the closeness of a relationship is judged based on the similarity level of the geometrical pattern of a sequenced curve. This is explained in more detail below.

Suppose $X$ is a collection of sequences comprising $n$ entries, and including $X_0$ which is a sequence of system characteristic behaviours called the ‘mapping quantity’ of a system’s behaviour, and $X_i$ are the behaviour sequences to be compared with $X_0$ (Chang et al., 2004). The key expression of the incidence coefficient of $X_i$ with respect to $X_0$ at point $k$ is defined as:

$$\gamma_{0i} = \gamma(X_0(k), X_i(k))$$,  \hspace{1cm} \text{.............. (5.10)}$$

$$\gamma_{0i} = \frac{\min_i \min_k |x_0(k) - x_i(k)| + \zeta \max_i \max_k |x_0(k) - x_i(k)|}{|x_0(k) - x_i(k)| + \zeta \max_i \max_k |x_0(k) - x_i(k)|}, \hspace{1cm} \text{.............. (5.11)}$$
where $\zeta \in (0,1)$ is called distinguishing coefficient, and $\gamma(X_0, X_i)$ is the degree of $X_i$ grey incidence with respect to $X_0$ and is defined as:

$$\gamma(X_0, X_i) = \frac{1}{n} \sum_{k=1}^{n} \gamma(x_0(k), x_i(k)). \quad \text{............... (5.12)}$$

After the degrees of grey incidence have been assigned, the grey incidence order is determined. The grey incidence order reflects the relative position between $X_0$ and $X_i$. Given the priori information of the well production classifications, the study area is classified by the grey rational analysis to classify the study area based on the similarity to the three production classifications: high, medium, and low. Wells A21, A15, and A03 were selected as being representative in this analysis. The result of the grey rational analysis is shown in Figure 5.7.
Figure 5.7 The result of the grey rational classification based on production. The unsmoothed result is shown in the upper panel (top); the smoothed result is shown in the lower panel (bottom). The result represents the high, medium, and low producing zones by red, green, and blue, respectively. The x-axis and y-axis of these map-view results are the distance in kilometres.
Table 5.1  Four types of information are shown for each well (columns from left to right): the time level in millisecond, data, model, and the grey attribute value. Higher deviations from zero value are marked by red in the fourth column for each well information table which indicates potential hydrocarbon presence.
5.4 CONCLUSIONS

The grey method derives its prediction based on the internal structure of the seismic trace, and is therefore assumed to yield results with lower uncertainties than traditional methods that require additional information such as well logs, core data and a geological model. The ‘grey attribute’ is proposed as an indicator to highlight the productive zones of the carbonate reservoir. The grey method reflects the characteristics of seismic data structure, providing a useful method for highlighting the relationship between seismic data structure and hydrocarbon distribution in petroleum-bearing reservoirs. The prediction process is strictly controlled by the time sequence data. Initial 1-D modeling results generated high deviation values which may indicate hydrocarbon existence. To validate this possibility, the well production classification was overlaid on the 2-D modeling results from the different reservoir levels. Interestingly, the validity of the approach was clearly demonstrated by the fourth time slice (936 ms), where there was a consistent match between the grey result and the well production classification. The grey 2-D modeling also highlighted anomalies on other time-horizon slices. It can be seen that analyzing the grey characteristics values of the seismic trace data structure allows the hydrocarbon accumulation of the reservoir to be highlighted. The method also helped to identify the main production layer.

By analyzing the internal structure of a seismic trace using the grey method, the zones of hydrocarbon accumulations can be inferred. The new method can help to highlight the reservoir hydrocarbon accumulation and should be particularly useful for carbonate reservoirs. Therefore, the grey attribute approach was found to provide useful information for reservoir exploration, and can be tested
using different field data for consideration as a new tool to characterize the reservoir and to increase the drilling success ratio (decrease the drilling risk) for new/planned well locations.
CHAPTER 6  LITHOFACIES CLUSTERING OF THE CARBONATE RESERVOIR USING KOHONEN SELF-ORGANIZING MAP

“The important thing is not to stop questioning. Curiosity has its own reason for existing. One cannot help but be in awe when he contemplates the mysteries of eternity, of life, of the marvelous structure of reality. It is enough if one tries merely to comprehend a little of this mystery every day. Never lose a holy curiosity”

(Albert Einstein)

A key goal in seismic reservoir exploration is to visualize unanticipated yet meaningful patterns within the data. One of the challenging issues for reservoir characterization is to accurately map the spatial distribution of reservoir heterogeneity. When 3-D seismic data is available, the artificial neural networks (ANN) approach is distinct from other conventional approaches in terms of its classification and prediction capabilities. This chapter develops and implements a neural network technique for characterizing the carbonate reservoir within the study area by mapping the reservoir lithofacies distribution using the Kohonen self-organizing feature map (KSOM). KSOM is one of recent advances in visualization technology which is applied in this chapter as one of the unsupervised neural network approaches; data clustering/classification is treated as an output data set without the need for any a priori information about the data. The algorithm was then enhanced to process multiple input-attributes.
6.1 INTRODUCTION

In the statistical literature, exploratory data analysis (EDA) is traditionally defined as “a data-driven search for statistical insights” (Hoaglin, 1982; Jain and Dubes, 1988; Tukey, 1977; Velleman and Hoaglin, 1981). EDA can be used as a powerful tool for knowledge discovery in databases (KDD) (Fayyad, 1996; Fayyad et al., 1996a; Fayyad et al., 1996c; Simoudis, 1996). In this established field, the emphasis is on the complete interactive process of knowledge discovery of features or structures in the data. One step in the discovery process is ‘data mining (DMD)’ which has different types of goals: pattern recognition (Devijver and Kittler, 1982; Therrien, 1989; Schalkoff, 1992); machine learning (ML) (Forsyth, 1989; Langley, 1996); and multivariate analysis which can be useful for analysing the data (Hair, Jr. et al., 1984; Kendall, 1975). Therefore, the novelty in this field lies in elucidating the hidden structure in a large database.

The Self-Organizing Map (SOM) approach has proved to be a valuable tool in DMD and in KDD, with various diverse applications. For example, since it was first developed in 1989, the Kohonen Self-Organizing Map (KSOM) has demonstrated its powerful capabilities in data visualization, data mining, image analysis, speech recognition, industrial process control, DNA sequencing, and others (Bryan, 2006; Chon et al., 1996; Schmuker et al., 2007; Back et al., 1996; Martin-del-Brio and Serrano-Cinca, 1993; Ultsch, 1993b; Ultsch and Siemon, 1990; Kohonen, 1997).

Accurately mapping reservoir heterogeneity and properties is one of the main tasks in characterizing a reservoir. The SOM approach has the advantage of visualizing the reservoir lithofacies non-linearity, which is not possible with other conventional methods. Previous reports have shown that these conventional methods sometimes fail to accurately classify the reservoir or to
estimate its properties due to the reservoir complexity, especially when faced with the exploration challenges associated with carbonate reservoirs. The heterogeneous nature of carbonate reservoirs adds a complexity that can prevent accurate results from being obtained with conventional techniques; therefore, the neural network approach is utilized here to handle the reservoir complexity.

This chapter develops the Kohonen Self-Organizing Map (KSOM) algorithm and implements it on the study area to resolve the reservoir complexity by self-organizing the internal structure of the reservoir through a competitive learning rule. Presenting the data set in an easily understandable form, whilst also preserving as much of the essential information in the data as possible, is one of the main goals of this chapter. KSOM also illustrates the clustering capability to classify the reservoir lithofacies heterogeneity. Searching, recognizing and classifying the internal structure of 3-D seismic data has been achieved in the past using a Kohonen neural network, and is shown to be successful in the present application (Taner et al., 2001; Walls et al., 2002).

6.2 KOHONEN SELF-ORGANIZING MAP METHOD

The algorithm was introduced by Professor Teuvo Kohonen in 1982 (Kohonen, 1981; Kohonen, 1982n). In a later paper, Kohonen (1990) provided a comprehensive review of the algorithm and related subjects. A SOM is a typical artificial neural network model and algorithm that implements non-linear feature projection from the high-dimensional input space into a low dimensional output space (feature space) comprising a 2-D array of neurons arranged in an orderly fashion (Kohonen, 1989; Aras et al., 1999). This ordered final output is a feature that distinguishes the SOM from the other neural
networks. The ordered mapping approach ensures that similar patterns in the input space are located near each other in the SOM space, and yields some advantages when compared with other neural network architectures. For example, it tends to preserve topological relationships and statistical properties of the data distribution in the input space (Aras et al., 1999; Huntsberger and Ajjimarangsee, 1990; Jang et al., 1997).

The SOM method has the ability not only to reduce the dimensionality and self-organization of the data, but also to cluster, classify and visualize the data through unsupervised learning, thus making it a valuable tool for characterizing (clustering and visualizing) the reservoir heterogeneity. Unlike other data mining/clustering tools which are of a symbolic, nonparametric nature, the SOM is a numerical approach that treats the data quantitatively in order to represent graded relationships by learning without supervision. The term ‘nonparametric’ is used here in the sense that no assumptions about the distribution of the data need to be made (Kohonen, 1995 a and b). Unlike other traditional clustering methods, the SOM is unique in that it reduces the amount of data by clustering, and simultaneously projects the data non-linearly onto a lower-dimensional display.

One important advantage of SOM is its increased effectiveness in clustering high-dimensional data relative to other methods. One of its disadvantages is the time-consuming process of determining the optimized value for its parameters. If the parameters are not optimized, individual SOM runs often yield different results.

### 6.2.1 Foundation for the SOM

Originally, the SOM was inspired by biological studies: most notably physiological studies which found that some sensory processing areas in the
brain are organized spatially according to the input stimulus (Knudsen et al., 1987).

Some of the early papers on SOM research attempted to map the organization of the cerebral cortex; these were followed by further developments and ended with a series of papers on the theory and applications of the artificial neural network algorithms (Anderson et al., 1990; Hecht-Nielsen, 1990).

The orderly topographical arrangement of sensory and motor neurons with similar response properties across the cortical surface is a central organizing principle in the mammalian cerebral cortex (Kohonen, 1982a). Based on lesion studies and electrical stimulation, anatomical evidence for cortical maps has been available since the nineteenth century (Kohonen, 1988). Topographically organized computational maps exist in different areas of the brain, such as the auditory, motor control and vision areas (Goodman and Shatz, 1993). In the 1960s, methods for recording from single cortical neurons were developed, and it became possible to determine how neurons were organized in the cortex (Goodman and Shatz, 1993).

Based on recordings from neurons in the somatosensory cortex, Vernon Mountcastle was the first to report that all neurons in a vertical column tend to have the same properties (Kohonen, 1988). In the visual cortex, David Hubel and Torsten Wiesel reported smooth changes in the response properties of cortical neurons (Hubel and Wiesel, 1962). Cortical maps have since been found and characterized in nearly all of the sensory and motor areas of the brain. In the visual cortex, the cortical maps have been the focus of studies into activity-driven mechanisms for synaptic plasticity and their interplay with non-activity-dependent processes based on cell adhesion molecules and diffusible substances (Goodman and Shatz, 1993). The single-unit recording techniques have been developed into new imaging methods which have helped to monitor the distribution of neuronal selectivity across the cortex; these have allowed
investigation of the large scale development of neuronal response properties with a greater coverage (Quartz and Sejnowski, 1997). A series of computational studies attempted to explain the structure of the cortical maps by simulating and analysing cortical models. One set of models was based on Hebbian learning and intracortical competition, which are concerned with mechanisms underlying development and plasticity. Results from this set were able to explain many features of the experimentally observed spatial patterns, despite their simplicity (Kohonen, 1982a). Another set was concerned with the computational advantages of the cortical maps (Durbin and Mitchison, 1990; Nelson and Bower, 1990). Additional approaches aimed at efficient coding have attempted to explain the properties of receptive fields and their spatial arrangement in terms of the statistics of the signals and the noise (Barlow, 1961; Field, 1994; Atick, 1992; Ritter et al., 1991). Most of these modeling studies were less successful in explaining the spatial layout of the maps. There is still no good explanation for why the cortex has such a regular structure. Using biologically inspired models, the SOM consists of functionally independent units in a parallel computational.

6.2.2 Architecture

The KSOM network architecture has two main layers: the input and computational layers. These layers form a feed-forward structure from the input layer in the input space to the computational layer in the feature space. The input layer presents different input patterns (training patterns) to the network, so the network learns from these patterns, then generalize for new patterns. The computational layer, also referred to as the output layer, consists of nodes (sometimes called neurons) that are regularly spaced and arranged in a rectangular grid. The neurons, also called units, represent the inputs with
reference vectors \((m_i)\), the components of which correspond to synaptic weights.

Both layers are fully connected and each connection is given an adjustable weighting. The processing ability of the neural network is stored in the inter-unit connection strengths, or weights, obtained by a process of adaptation to, or learning from, a set of training patterns or examples (Wong et al., 1995). The weight adjustment is determined only by its learning rate and the difference between the input pattern and the neuron which is closest to it (the winner).

### 6.2.3 Algorithm Summary

To enable practical implementation of the algorithm, some approximations to simplify the biologically-inspired system were made. These comprise two steps that are iterated for every input pattern: (1) finding the best matching units (BMU) by unsupervised, competitive learning, and (2) adapting the weights. The algorithm is characterized by unsupervised training and competitive learning. The algorithm is classified as an unsupervised training network because it learns by itself (self-organizing) without the need for external guidance (or teacher).

The SOM is a branch of unsupervised learning techniques aimed at determining the statistical properties of input data without explicit feedback from a teacher, and is one of the most widely-used algorithms in the unsupervised learning category (Rappa et al., 1992). The algorithm also includes competitive learning, which is an adaptive process whereby the neurons in a neural network gradually become sensitive to different input categories of the input space (Grossberg, 1976; Kohonen, 1982; Kohonen, 1984; Nass and Cooper, 1975).
When an input pattern $x(t)$ is introduced to the network, the competition among neurons (which are located on a discrete lattice) is enforced. The unit, denoted by $c$, whose reference vector is nearest to the input $x$, is the winner of the competition.

$$c = c(x) = \min_i \| x(t) - m_i(t) \|^2$$ .......................... (6.1)

The competitive learning algorithm allows not only the winning neuron, but also its neighbors on the lattice to learn. The values of the weight vector $m_i$ are adaptive so that the match between the modified weight vectors in the active area (in the neighbourhood of the best matching unit) and the input vector $x(t)$ become closer.

The winning unit and its neighbors adapt to improve representation of the input by modifying their reference vectors towards the current input. The amount by which the units learn is governed by a neighborhood kernel $h$, which is a decreasing function of the distance of the units from the winning unit on the map lattice. If the locations of units $i$ and $j$ on the map grid are denoted by the two-dimensional vectors $r_i$ and $r_j$, respectively, then

$$h_{ij}(t) = h(\| r_i - r_j \|, t)$$ ................................. (6.2)

where $t$ denotes time.

During the learning process at time $t$, the reference vectors are changed iteratively according to an adaptation rule (Luttrell, 1990; Kohonen, 1993) as follows:

$$m_i(t+1) = m_i(t) + h_{ci}(t)[x(t) - m_i(t)]$$ .......................... (6.3)

where $x(t)$ is the input at time $t$ and $c = c(x(t))$ is the index of the winning unit.

The learning process, consisting of winner selection defined by Equation (6.1) and adaptation of the synaptic weights defined by Equation (6.3), can be
modelled with a neural network structure in which the neurons are coupled by inhibitory connections (Kaski and Kohonen, 1994).

The neighbourhood function can be defined freely. The traditional (simplest) neighbourhood kernel is a fixed size neighbourhood around node $c$:

1. **Traditional,**

   $$ h_{ci} = \begin{cases} 
   1, & \text{if } \|r_i - r_c\| < s(t) \\
   0, & \text{otherwise} 
   \end{cases} $$

   where $s(t)$ is a decreasing function of time.

2. **General,**

   A widely applied kernel function (which is implemented in this work) is expressed in terms of a **Gaussian neighbourhood** function:

   $$ h_{ci} = \alpha(t) \exp\left(\frac{-\|r_i - r_c\|^2}{\sigma(t)^2}\right) \quad \text{.................................. (6.4)} $$

   where $\alpha(t)$ and $\sigma(t)$ are the learning rate parameter and the width of the kernel, respectively. Both are monotonically decreasing functions of time. The resulting mapping from the input (signal) space to the SOM (surface) space is ordered after automatically adapting the processing units in the input signal by the competitive learning.

   Based only on the internal relations within the structure of the input signal, the ordering takes place automatically without external supervision, so the algorithm creates an internal representation of the incoming signal structure which ensures that similar patterns in the input space are correspondingly located near each other in the SOM space. This unsupervised neural network therefore relies on varying network topologies and adjustment parameters such
as initial neighbourhoods, decay functions and step size to suitably control the internal learning.

6.2.3.1 Ordered Display Property

The SOM, by virtue of its learning algorithm, forms a non-linear regression of the ordered set of reference vectors onto the input space. In fact, the ‘topography-preserving’ ability of the SOM is an important property that is utilized within the DMD and EDA process. This key characteristic allows the mapping of multidimensional input onto a lower dimensional output, usually in 2-D form. In general, the input data of a high-dimensional data set is taken by the SOM model to establish the non-linear statistical relationships and to transform the data into a topology-preserving geometric structure in low-dimensional form (Kohonen, 2001).

Kohonen (1981) proposed that the SOM should illustrate the analysis of a data set in an ordered display. The ordered nature is an important property of the SOM map in understanding the structures in the data set and helps the analysts to interpret the information in a fast and easy way. The smoothed and organized appearance of the variables in the SOM display helps in gaining insight into the distributions of their values in the data set. Such displays are much more illustrative than in other statistical methods.

6.2.3.2 Visualization Property

Discovering structures in large multidimensional data sets can be difficult and time consuming. Output from the Kohonen SOM is typically displayed in a 2-D
map to aid exploration of structures within data sets. The algorithm is therefore an efficient tool, not only for grouping the data, but also for visually identifying features (Ritter et al., 1992).

The SOM ordered display can also be used for illustrating the clustering density of the data; the density of the input samples can be reflected by the density of the reference vectors of an organized map (Ritter, 1991). The reference vectors will be close to each other in the clustered zones of the SOM display, so there can be sparse regions between clusters. The distances between reference vectors of neighboring units can be utilized to display the cluster structure in the data set (Kraaijveld et al., 1995; Ultsch, 1993b; Ultsch and Siemon, 1990). The first step in this process is to compute and scale the distance between each pair of reference vectors, so that the distances fit between a given minimum and maximum value (Iivarinen et al., 1994). The map then displays varying gray levels (or color levels) for the points. The gray level of a point corresponds to the mean of the nearest distance values of the points around it. The resulting cluster diagram does not require any assumption about the shapes of the clusters; thus, it is useful for data-driven feature selection, visualization and clustering of high-dimensional seismic data with applications in reservoir characterization.

6.3 KOHONEN SELF-ORGANIZING MAP FOR RESERVOIR LITHOFACIES MAPPING

Determining the lithology is one of the main tasks in characterizing the reservoir. Usually, the lithology is described by geologists from cuttings when drilling the well or from cores at the warehouse. This lithology description is very representative (accurate) at drilled well locations. Facies interpretation
from well logs is a second option, but is time-consuming, especially as the number of logs increases. Therefore, finding a better way of accurately estimating lithology in a timely manner is a key motivation of the present study. Adopting the assumption that changes in a reservoir’s lithology, rock properties and fluid content affect the seismic traces with respect to amplitude, shape and lateral coherency, gives the SOM the advantage of being able to detect and cluster the different traces characteristics representing the reservoir facies classes. This method can therefore provide information on inter-well lithology and is useful for mapping the dominant lithofacies in the reservoir and for defining their spatial boundaries. The SOM algorithm performs clustering based on the ‘winner takes all’ competitive learning technique. The advantage of using the Kohonen neural network is in its ability to classify and cluster the high-dimensional seismic data. SOMs learn to classify input vectors according to how they are grouped in the input space.

In general, the application of neural networks for reservoir characterization falls in one of two categories: classification and prediction (De Groot, 1998 and 1999). This part of the study focuses on the classification objective, where the aim is to generate clusters of lithofacies from seismic data. The Kohonen self-organizing neural network algorithm was coded, and implemented on the 3-D seismic data of the study area, with the aim of characterizing the carbonate reservoir using a SOM. The SOM clustered the reservoir heterogeneity (reservoir quality) to provide an indication of the reservoir’s main facies, as well as, identifying the spatial distribution of the facies boundaries.

The SOM was performed for two different cases depending on the input to the network: these were single and multiple inputs. The original amplitude volume was first used as the only input to the SOM analysis. Then, in the second case, the SOM algorithm has been enhanced to use four different seismic attributes as inputs to the SOM: instantaneous amplitude, instantaneous phase,
instantaneous, frequency and acoustic impedance. SOM input data were pre-processed by normalizing the data vectors such that vectors had unit length.

The SOM analysis entailed two main phases: (1) the training phase of the artificial neural network (SOM) (Figure 6.1), and (2) the mapping phase, in which not only were the training patterns presented, but also new patterns (that were not used in the training phase) were presented to the trained network for the purpose of clustering the data and revealing the hidden internal structure.

**Figure 6.1** The flowchart of the training phase showing four main stages in the following order: initialization, competition, cooperation, and adaptation.
6.3.1 Training Phase

A square grid of artificial neurons (nodes) was initialized to train the network. After different trials, the size of the network was chosen to be 40x40 nodes. Each node represents a weight vector of the same dimension as the node’s input pattern. The input space comprised a total of 160801 data points; each data point held 12 time samples. The weights were initially set to random values. In order to train the network, the network was fed with random input patterns in an iterative process. Random traces were selected as input to the network (Figure 6.2). This subset of input patterns corresponds to a small sub-area of the input space. Therefore, the feeding direction was from the high-dimensional input space to the SOM low-dimensional feature space.

Beginning with an initial state that corresponds to a completely disordered map, the goal of the algorithm is to arrive at a state that corresponds to an ordered, ‘topology-conserving map’ of the input space, in which selected relevant lithofacies features of input patterns are two-dimensionally represented.

At the beginning of the training phase, a large difference between the first randomly selected input pattern and its winning reference vector is expected. This difference gradually decreases during training as a consequence of the monotonically decreasing value of both the neighborhood radius and the learning rate (Figure 6.3). When the training starts, the neighborhood is broad and the self organizing takes place on a global scale. However, the neighborhood shrinks as the training continues, and the weight update converges to a local scale. Therefore, it is expected that network update of the weights of the winning node and surrounding neurons (within the initial radius) will have a high learning rate when the training starts, but eventually only the
weights of the winner will be updated, with a lower learning rate, in the last iteration of the training. Furthermore, the difference between the randomly selected input vector and its winner will become much smaller at the end of the training phase. Most of the nodes get the chance to be the best matching unit in the introduced patterns. Figure 6.4 shows the winning neurons and their frequency of winning. By the end of the training phase, not only is the difference much smaller, but also the resulting map is topographically self-organized (SOM), indicating that the network is trained and that the network is ready to map the whole input space data into the SOM feature space (Figure 6.5). The arrangement of neurons in the lattice reflects the arrangement of their respective structures in the input space.

Although the SOM is an important approach for exploratory data analysis, being regarded as a roadmap of the data space, it cannot provide a detailed interpretation and explanation of their structure without additional analysis.
Figure 6.2 Random input patterns used to train the network. The x-axis and y-axis are distance in kilometres.
Figure 6.3 Monotonically decreasing learning rate (top) and neighborhood function (bottom).
Figure 6.4 Count map of winning nodes.
6.3.1.1 U-Matrix Analysis

One way of visualizing the complexity of the hidden structures in the data is the U-matrix analysis. The term ‘U-matrix’ is short for unified distance matrix. The U-matrix is a tool for inspecting high dimensional data (Ultsch and Siemon, 1989), and is one of the techniques employed to visualize the SOM analysis based on the observation of the distances between the neurons’
reference vectors. The U-matrix technique calculates the weighted sum of all Euclidean distances between the weight vectors for all output neurons. The U-matrix value of a particular node is the average distance between the node and its closest neighbors (Ultsch et al., 1993). The U-matrix algorithm can be thought of as a mapping from $R^n$ to a non-linearly flattened two-dimensional surface, such that the topological relations are conserved. Geometrical closeness is adopted as a measure of similarity. The algorithm generates images in which the input data cluster structure can be visualized through the use of a third dimension in the form of walls. The display usually has ‘valleys’ where the vectors in the lattice are close to each other and ‘hills’ or ‘walls’ where there are larger distances, indicating dissimilarities in the input data. Therefore, if a subset of input data falls into a valley in the U-matrix, then it’s cluster contains similar vectors. If different subsets are separated by walls or hills, then there are larger dissimilarities the different clusters. This method allows easier detection of clusters than most classical clustering methods (Ultsch and Siemon, 1989). The result of the U-matrix analysis can add value to the interpretation of the clusters created by the SOM (Figure 6.6).
Figure 6.6 The U-Matrix map showing the major boundaries. Valleys and walls are dark color and light color, respectively.

6.3.1.2 K-Means Clustering

The SOM method is closely related to the partitioning method of the k-means type. The k-means algorithm is one of the common clustering algorithms (MacQueen, 1967); the k-means algorithm is an iterative procedure that compresses the data vectors into a smaller set of reference vectors based on
minimizing the error and assigning the nearest neighbor (Fritzke, 1993). The number of clusters needs to be chosen in advance before running the algorithm.

The main steps of the k-means algorithm are outlined as follows:
1- Defining the number of classes.
2- Initializing the same number of random guesses and considering them as cluster centers.
3- Classifying each clustered point.
4- Re-computing the estimates for each of the initial guesses using results of Step 3.
5- Repeating Steps 1, 2 and/or 3 until all the initial guesses are consistent and are not changing.

The output of the k-means clustering is representative traces for the main lithofacies categories (Figure 6.7). These traces are used in the mapping stage for the final lithofacies estimation of the study area data.
Figure 6.7  Representative traces for the main lithofacies clusters.

6.3.2 Mapping Phase

After developing the SOM algorithm and training the network, the goal of estimating the main lithofacies of the real 3-D seismic data was achieved through implementing the trained network on the data. In this stage, the network becomes associated with a continuous image of the input structure, as each input point corresponds to a point in the lattice (feature space) such that the relationships between neighbouring points are preserved. After running the algorithm on the data, the resulting maps predominantly represent those directions of the input space along which the input patterns change most
strongly. In the present study, the network showed a similar structure to the input, indicating that the network was well trained and capable of estimating the structure of the data (Figure 6.8). The difference between these two maps is minimal as shown on Figure 6.9.
Figure 6.8 The input attribute (top), and the result of the network mapping (bottom). The x-axis and y-axis are distance in kilometres.
Figure 6.9 The difference map between the input data and the network mapping. The x-axis and y-axis are distance in kilometres.

This is a result of the correspondence of each input point to a point in the lattice (feature space), which provides a representative well for the subsurface structure at that point. The lithofacies in the area are shown by Figure 6.10 and comprise nine main types.
Figure 6.10  The final lithofacies cluster map (using a single input) showing the spatial distribution of the nine main lithofacies within the study area. The x-axis and y-axis are distance in kilometres. One observation is that the low producing wells are covered by different clusters group than the other producing wells.

The results indicate that Facies 1 to 5 dominate the low-production wells (Wells A01, A03, A09, A18 and A20). These particular facies are expected to be non-hydrocarbon bearing facies (NHC-bearing) such as mudstone. On the other hand, Facies 6 to 8 are dominant near the intermediate- and high-
production wells (Wells A15, A17 and A21). Lithofacies such as grainstone, wackestone, and packstone are expected to represent these facies, due to their hydrocarbon-bearing (HC-bearing) properties. The observation that low producing wells fall within different cluster categories than those for the moderate and high producing wells is a validity measure for the success of the algorithm to generate representative clustering. The lithofacies map is therefore useful in future planning of well drilling.

A second trial of the SOM was run using multiple attributes input. The self-organizing network lithofacies mapping obtained when using instantaneous amplitude, instantaneous phase, instantaneous frequency and acoustic impedance as inputs is shown in Figure 6.11. In general, the results of a single input and multiple attributes show similarity of the general trends in the area, even though the color schemes are different.
6.4 CONCLUSIONS

The unsupervised Kohonen self-organizing neural network was developed, enhanced, and implemented on real 3-D seismic data for the purpose of clustering the reservoir’s dominant lithofacies within the study area. Unlike the supervised approach, the coded technique in this chapter analyse the internal structure of the data to discover the hidden pattern without any external
guidance. Overall, results of the competitive-learning SOM network indicated that the reservoir can be clustered around nine different lithofacies. One important observation was that the intermediate-production and high-production wells fell within different clusters to those of the low-production wells. This observation was noticed on both the single-input network, and the multiple-input network (enhanced network).

All in all, the Kohonen self-organizing neural network analysis and mapping were based on the internal structure of the 3-D seismic data. The result has revealed important information that can increase confidence in the planning of future drilling locations, thereby reducing the drilling risk. The developed methodology in this chapter is one of the most powerful techniques that contribute significantly in drilling risk reduction.
CHAPTER 7  PROPERTIES ESTIMATION
OF THE CARBONATE RESERVOIR USING
BACK-PROPAGATION NEURAL NETWORK

“The ideal reasoner, he remarked, would, when he had once been shown a
single fact in all its bearings, deduce from it not only all the chain of events
which led up to it but also all the results which would follow from it”
(Sherlock Holmes, in "The Five Orange Pips," by Sir Arthur Conan Doyle)

An important objective in characterizing a carbonate reservoir is to accurately
predict the spatial distribution of its geophysical properties. Mapping results
based on only well data are often inaccurate. More accurate characterization of
the reservoir requires the integration of data and knowledge from other data
types. Thus, the use of 3-D seismic data in addition to the well data plays an
important role in achieving this objective.

Artificial neural networks (ANNs) are capable of elucidating the nonlinear
relationship between seismic data (the input) and reservoir properties (output
parameters). In an attempt to explore this relationship, I implement a
supervised neural network which has the ability to learn from the well
information and then to generalize the relationship to inter-well areas. Two of
the most essential reservoir properties were estimated: porosity and
permeability. Validation of the results demonstrated the network to be a
powerful tool for hydrocarbon exploration.
7.1 INTRODUCTION

Accurate mapping of the spatial distribution of reservoir properties and heterogeneity is considered as a major objective in developing reservoir models. In recent years, increasing attention has been drawn to utilizing machine learning for characterizing subsurface reservoirs. This includes predicting the distribution of inter-well reservoir properties and heterogeneity. ANNs are one of the most popular techniques in soft computing. Many researchers have demonstrated that neural networks can assist engineers and scientists in developing a better and more realistic understanding of most important reservoir characteristics. An ANN can uncover inherent relationships in the reservoir after training the network using the well data; this relationship is then used to predict the reservoir characteristics such as porosity and permeability. Neural networks have been used to predict reservoir characteristics, such as porosity, permeability and fluid saturation, from conventional well logs (Mohaghegh et al., 1996; Huang et. al., 1996). The utilization of an ANN to obtain relationships between seismic data and geological properties can be very valuable due to the complexity of reservoir characteristics and the limited availability of well data. There are other applications of ANNs in reservoir characterization, such as in fractured reservoir studies (Quenes, 2000), and in hybrid neural network implementation (Aminzadeh, et. al., 2000).

This Chapter integrates 3-D seismic data and well data to determine two important reservoir physical properties (porosity and permeability) using a back-propagation neural network (BPNN). While BPNNs have already been successfully applied to the area of log analysis (Wong et. al., 1995), this study focuses on inter-well prediction based on 3-D seismic data.
7.2 BACK-PROPAGATION NEURAL NETWORKS

Most of today’s computer systems have been designed to perform mathematical and logic functions at speeds that are incomprehensible to humans (Rogers et al., 1995). Mathematical prowess is not always needed to recognize different patterns in complex systems. However, when dealing with large input data, the time become intolerable. A system that is able to adapt itself to learn the relationship from few example patterns, then generalize the relationship to new patterns would be an ideal approach. Fortunately, such a system is known as back-propagation artificial neural network (BPNN).

Research into parallel distributed processing (PDP) led to the development of the back-propagation neural network (BPNN) (Rumelhart and McClelland, 1986; Maloney, 1989). The work of Rumelhart et al. (1986), Parker (1985), and Werbos (1974) has provided the foundations of this useful class of artificial networks.

7.2.1 Architecture

The architecture (topology) of the multi-layer perceptron network consists of three layers: input, hidden and output. The input layer is a non-processing task layer containing artificial neurons or so-called processing elements (PEs) (which can also be called nodes) for each input variable; the number of neurons in this layer corresponds to the number of inputs that are being presented to the network. A single hidden layer is a processing layer with a non-linear activation function. The neurons in this layer are responsible primarily for
feature extraction (Levine, 2000). This layer is sufficient to approximate a continuous function with arbitrary precision (Cybenko, 1989). The function of the hidden layer is to intervene between the input and the network output. There are five nodes in the single hidden layer which are fully connected to all input units and to the node in the output layer. The output layer contains one node for each output value (the proposed network has one node). The overall response of the network is achieved through the final layer (Haykin, 1999). A schematic diagram of the network topology is shown in Figure 7.1, and a flowchart depicting the main steps of the proposed approach in the present study is shown in Figure 7.2.
Figure 7.1 The topology of the proposed neural network. The input layer, hidden layer, and output layer have four nodes, five nodes, and one node, respectively. The signal direction starts from the input layer, through the hidden layer, and ends at the output layer. The error back-propagation direction is from the output layer, through the hidden layer, to the input layer.
Figure 7.2 The flowchart of the proposed approach showing three main phases: preparation, training, and application. The application phase starts after the network is trained.
7.2.2 Back-propagation Algorithm

The back-propagation algorithm is a first-order approximation of the steepest descent technique in the sense that it depends on the gradient of the instantaneous error surface in weight space (Haykin, 1999). Error back-propagation algorithm is a supervised learning model. In other words, it is trained with both input and desired output (target) data. The training set must be carefully selected to contain representative examples encompassing the appropriate variance over all relevant properties for the problem at hand (Goodzere et al., 1998). The Back-Propagation (BP) training algorithm is a gradient-based optimization algorithm which is considered as the most commonly used learning algorithm for neural networks. The back-propagation neural network is a multi-layer feed-forward neural network trained by the generalized delta rule (GDR) (Rumelhart, 1986). The key principle of the algorithm is that the errors for the nodes are determined by back-propagating the errors of the nodes of the output layer; this process gives the back-propagation neural network its name.

By using a two-phase propagate-adapt cycle, the network learns a predefined set of input-output sample pairs (Figure 7.3). After the input data are provided to the first layer (input layer) of a network unit, they are propagated through each upper layer until an output is generated. This output is then compared to the desired output, and an error signal is computed for each output unit. Next, the error signals are transmitted backward from the output layer to each node in the hidden layer that contributed directly to the output. However, each unit in the hidden layer receives only a portion of the total error signal, based roughly on the relative contribution the unit made to the original output.

This process repeats layer by layer, until each node in the network has received an error signal that describes its relative contribution to the total error. Based
on the error signal received, connection weights are then updated between each unit, to cause the network to converge toward a state that allows all the training sets to be prearranged. This process is significant because, as the network trains, the nodes in the hidden layer organize themselves such that different units learn to recognize different features of the total input space, so that the network develop internal relationships among nodes so as to organize the training data into classes of patterns (Geoffrey and Sejnowski, 1987).

‘Learning’, in a neural network, means finding an appropriate set of weights. Learning is accomplished by adjusting the network weights until the differences between the actual and desired output are acceptably low. The process of adjusting the weight values is known as training. Training can be a lengthy process, and there is no guarantee that the network will reach the desired outputs; however, the network will usually give outputs within some error tolerance (Rogers et al., 1995). The network can be trained with as many data as available, although there is no need to use all the data. A comprehensive sampling of the data can be sufficient; the training data should cover the entire expected input space. After training, different nodes learn how to recognize different features within the input space and weights in the network become efficient recognizers of new patterns introduced to the network.

There are four main parameters controlling the error back-propagation algorithm: (1) learning rate, (2) momentum, (3) epochs, and (4) error limit. The learning rate tells the network by how much the weights are adjusted at each learning step; it is usually in the order of 0.05 to 0.45. Momentum is used to increase learning speed; it is usually set to a positive value less than 1. Epochs control how the network processes many times the whole set of input vectors. The error limit controls when to stop training.
Figure 7.3 The back-propagation direction is opposite to the signal feed direction (activation direction). Summation and activation function are two main operation for each node in the hidden and output layers. The ‘Tangent Hyperbolic’ activation function is used in this study.

7.2.2.1 Activation Functions

The activation function of a node defines the output of that node given an input or set of inputs. The activation function, also known as the transfer function, is one of four basic elements of the neural network model (Figure 1.A2). The other three elements are synapses, an adder, and a threshold. The synapses receive the signal; the adder sums the input signals which are weighted by the respective synapses; the threshold is applied externally; and the activation
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function limits the amplitude of the output of a neuron within a normalized value in a closed interval, say, within \([0, 1]\) or \([-1, 1]\). The activation function rescales the output signal so that it lies in a 'permissible' (amplitude) range (Figure 7.4).

When a neuron \(j\) updates the weights, it passes the sum of the incoming signals through an activation function (transfer function). Mathematically, a neuron \(j\) has two Equations that can be written as follows:

\[
\text{NET}_{pj} = \sum_{i=1}^{N} w_{ji} x_{pi} \hspace{1cm} \text{(7.1)}
\]

and

\[
y_{pj} = \varphi(\text{NET} - \phi_{pj}) \hspace{1cm} \text{(7.2)}
\]

where \((x_{p1}, x_{p2}, ..., x_{pN})\) are the input signals and \((w_{j1}, w_{j2}, ..., w_{jk})\) are the synaptic weights of neuron \(j\). \(\text{NET}_{pj}\) is the linear combiner output, \(\phi_{pj}\) is the threshold, \(\varphi\) is the activation function and \(y_{pj}\) is the output signal from the neuron. The dot, or inner, product of these two vectors (input signal and synaptic weights) represents the total input signal.

Geometrically, the total signal can be considered as a measure of the similarity of these two vectors.

The physical meaning of the activation function is to mimic the biological output in generating or not generating the signal. This decision is made by comparing the weighted sum (generated by the summation function) with a threshold. If the sum is greater than the threshold value, a signal is generated by the processing element. Otherwise, no signal is generated.

Depending on the particular network, different activation function types can be applied, including: a simple threshold function, the Gaussian function, the sigmoid function, and the hyperbolic function (Table 8.1). In general, the activation function can be either linear or non-linear. However, it is the non-
linear activation function that allows such networks to compute nontrivial problems using only a small number of nodes. Figure 7.4 shows some of the common activation functions.

The threshold function is not differentiable; therefore, it is not widely used. The $k$ in the threshold type is a constant threshold function, i.e.

$$y_{pj} = \begin{cases} 1 \text{...if } (\text{NET})_{pj} > T \\ 0 \text{...otherwise} \end{cases}$$

$T$ is a constant threshold value, or, as proposed by the McCulloch and Pitts (1943) model, a function that permits more general network functions which stimulate more accurately the non-linear transfer characteristics of the biological neuron. $\sigma$ in the second transfer function (the Gaussian function) is the standard deviation of the function. $a$ in the third transfer function (sigmoid function) is the slope parameter of the function. Different sigmoid function slopes are obtained by varying the slope parameter. The sigmoid function applies a certain method of compressing the range of $NET_{pj}$ to a limit that is never exceeded by $y_{pj}$.

The hyperbolic function is symmetrical about the origin and looks like the sigmoid function in terms of shape. In a multilayer perceptrons network, the sigmoidal and hyperbolic activation functions are most commonly used.
<table>
<thead>
<tr>
<th></th>
<th>Activation Function</th>
<th>Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Threshold function</td>
<td>( y_{pj} = k(NET)_{pj} )</td>
</tr>
<tr>
<td>2</td>
<td>Gaussian function</td>
<td>( y_{pj} = ce^{-\frac{NET_{pj}^2}{\sigma^2}} )</td>
</tr>
<tr>
<td>3</td>
<td>Sigmoid function</td>
<td>( y_{pj} = \frac{1}{1 + e^{-a \times NET_{pj}}} )</td>
</tr>
<tr>
<td>4</td>
<td>Hyperbolic function</td>
<td>( y_{pj} = \tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} )</td>
</tr>
</tbody>
</table>

**Table 7.1** Common types of activation functions: Threshold function, Gaussian function, Sigmoid function, and Hyperbolic function.
Figure 7.4 Some activation functions; the ‘Tangent Hyperbolic’ function (circled in red) is used in this study. The output of this function is values between ‘-1’ and ‘+1’.
7.2.2.2 Generalized Delta Rule

The ‘Delta rule’ is based on the idea of continuously modifying the strengths of the connections between nodes to reduce the difference (Delta) between the desired output and the calculated output values of a neuron (Statsoft Inc., 1997). Unlike the Delta rule, which uses local error information, the ‘Generalized Delta rule (GDR)’ utilizes global error information (global minimum of the mean square error (MSE) on the training set), so it is designed to minimize the total of the squared errors of the output nodes. This is achieved by using the steepest descent method.

The optimization method attempts to find the most suitable values of weights for a global minimum in the mismatch between the desired target pattern and its actual value for all of the training examples (Figure. 7.5). The degree of mismatch for each input-output pair is quantified by solving for unknown parameters between the hidden and output layer and then by propagating the mismatch backward through the network to adjust the parameters between the input layer and the hidden layer. Suppose the network has an input layer that contains an input vector:

\[ x_p = (x_{p1}, x_{p2}, \ldots, x_{pN})^T \]  

(7.3)

The input units distribute the values to the units. The net output to the \( j^{th} \) hidden layer unit is:

\[ NET_{pj}^h = \sum_{i=1}^{N} w_{ji} x_{pi} + \theta_{j}^h \]  

(7.4)

where \( w_{ji} \) is the weight of the connection from the \( i^{th} \) input unit, \( \theta_{j}^h \) is the bias term and \( h \) is a subscript referring to the quantities on the hidden layer.
The output of this node (assuming that the activation of a node is equal to the net input) is

\[ i_{pj} = f^h_j(NET^h_{pj}) \]  \hspace{1cm} (7.5)

The output nodes Equations are:

\[ NET_{pk}^o = \sum_{j=1}^{L} w_{kj}^o i_{pj} + \theta_{k}^o \]  \hspace{1cm} (7.6)

\[ o_{pk} = f^o_k(NET_{pk}^o) \]  \hspace{1cm} (7.7)

where the \( o \) superscript refers to quantities on the output layer.

The mathematical derivation for updating the weights of the hidden and output layers is included in Appendix 7.A.

In general, the weights are adjusted through the following equation to reduce the error (Rumelhart et al., 1986):

\[ \Delta w(t) = -\alpha \frac{\partial E}{\partial w(t)} + \beta \Delta w(t-1), \]  \hspace{1cm} (7.8)

where \( \alpha \) and \( \beta \) are assumed constants, called the learning rate and momentum factor, respectively, \( E \) is the error function, \( w \) is the weight vector, and \( t \) is the iteration number.

\[ 7.2.2.3 \hspace{0.5cm} \text{Stopping Criteria} \]

Kramer and Sangiovanni-Vincentelli (1989) formulated a sensible convergence criterion for back-propagation learning, whereby the back-propagation algorithm is considered to have converged when:
1. The Euclidean norm of the gradient vector reaches a sufficiently small gradient threshold.

2. The absolute rate of change in the average squared error per epoch is sufficiently small.

3. The generalization performance is adequate, or it is apparent that the generalization performance has peaked.

**Figure 7.5** The generalized delta rule optimization method attempts to find the most suitable solution (ideal solution). This 3-D sketch shows the mechanism of updating the initial weight vector through the first update step (delta vector) toward the final ideal weight vector location.
7.2.3 The Basic Training Steps

The basic procedure for training the network is summarized as follows:

1. Apply an input vector to the network and calculate the corresponding output values.
2. Determine the measure of error by comparing the actual outputs with the outputs.
3. In order to reduce the error, determine in which direction (positive or negative) to change each weight.
4. Determine the amount by which to change each weight.
5. Apply the correction to the weights.
6. Repeat Steps 1 to 5 with all the training vectors until the error for all vectors in the training set is reduced to an acceptable tolerance.

7.3 IMPLEMENTATION

7.3.1 Method

The learning process of a neural network is executed by optimization algorithms. The back-propagation (BP) algorithm is powerful and commonly used for multi-layer perceptron (MLP) network (Rosenblatt, 1962; Rogers et al., 1995). As a feed-forward neural network with supervised learning, it is also one of the most popular approaches for modelling and computer learning (Looney, 1997). The back-propagation algorithm is fully developed and mature and employs an iterative gradient-descent technique which is used to estimate neural connection strengths (the coefficient) by minimizing an error function (Bishop, 1995; Kosko, 1996; Haykin, 1999).
As discussed above, the error back-propagation algorithm consists of two passes: a forward pass and a backward pass. In the forward pass, an input vector is supplied to the first layer of the network and propagates forward layer by layer. On reaching the last layer (output layer), an output is produced as the response of the network. During this forward pass, the synaptic weights of the network are all fixed. This output is compared with the desired output. In the subsequent backward pass, the weights are adjusted in accordance with the error-correction rule. The difference (error) between the actual and the desired value is propagated backward through the network against the direction of synaptic connections. This process is continued in an iterative manner. The network converges when its output is within an acceptable range from the desired output. The computational capabilities of the network are sufficient for learning input-output mapping between patterns (Omlin and Giles, 2000).

7.3.2 Petrophysical Prediction from Seismic Attributes

In general, the application of neural networks for reservoir characterization falls into one of two categories: classification and prediction. This part of the study focuses on the prediction objective, where the aim is to predict (one or more) continuous petrophysical parameters from seismic data (Schultz et al., 1994; Todorov et al., 1998). A three-layer back-propagation neural network with five hidden neurons in the middle layer, and a hyperbolic tangent (tanh) activation function in all hidden and output neurons, is developed for predicting selected important reservoir properties (porosity and permeability) using pairs of input-output samples. Figure 7.1 is a schematic diagram of the developed three-layer neural network.

In order to implement the BPNN, the network has to undergo two main modes (training and application (production)) that perform the following three steps:
(1) PREPARING THE DATA: Network training depends primarily on the prior knowledge available in the application domain. A collection of input-output pairs from the well locations can train the network; different training sets can be identified. All data points are normalized then separated into training set and production set.

(2) TRAINING THE NETWORK: In response to a given input, neural networks are trained to produce a certain output. The training of a network consists of adjusting and readjusting the weights until the desired response is produced. The normalized input data are fed from the input layer directly to the hidden layer and then passed to the output layer. While this feeding process is taking place, each node (or PE) receives the sum of the weighted output of the previous layer, passes the sum to the transfer function and produces the node output signal. This output is used as the input to several other PEs in the next layer, unless the stimulating PE is located at the network output. For each training instance, the final output value of the network is compared with the desired output value. The difference between the system output and the desired output value is adjusted by a generalized delta rule (Berry and Linoff, 1997).

(3) PREDICTING THE RESERVOIR PROPERTIES: During the training mode, the BPNN is trained to establish the relationship between seismic attributes and the desired reservoir properties. Only data at the well location (or near the well locations) are used for the network training. After training the network, the network is used in application/production mode where the input data from the whole study area pass through the trained network to yield the distributions of the desired properties.
7.3.3 Data and Analysis

The 3-D seismic data and the log information for the eight wells within the 40x40 km area were used in this study. The target of the analysis was a carbonate reservoir. The aim of the analysis was to accurately predict and spatially map some of the reservoir properties (porosity and permeability).

The four seismic attributes (instantaneous amplitude, instantaneous phase, instantaneous frequency and acoustic impedance) were the inputs to the network, which was configured to estimate the porosity. The porosity samples were then used as the main input to the network to estimate permeability. The porosity was first estimated, and then used to predict the permeability. Porosity and permeability not only share their importance for characterizing a reservoir, but also have close relationship. Usually, the higher the porosity, the higher the permeability, but this is not always the case.

7.3.4 Results and Validation

The network was first trained using the input/output pairs at the eight well locations. Four input attributes (instantaneous amplitude, instantaneous phase, instantaneous frequency and acoustic impedance) were normalized and fed into the developed network in order to estimate the reservoir porosity. The correlation coefficient between the original porosity values at the well locations and porosity values estimated by the BPNN ranged between 67% and 97% (Table 8.2). Predicted results are shown in Figure 7.6, which compares the target porosity (black curve) with the estimated porosity (grey curve) at each of the eight well locations. The overall correlation coefficient was approximately
85%. The next step was to generate the 2-D porosity mapping at the different reservoir levels; however, a validation of the result was needed before generating these 2-D maps to ensure that the network was generalizing and not over-fitting.

**Figure 7.6** A comparison between the target porosity log (black solid curve) and the network porosity prediction (gray curve) for each of the eight well locations. The x-axis and the y-axis are the porosity and time, respectively.
Over-fitting, also referred to as ‘memorization’, could be a common problem in the prediction of a neural network. Once a network memorizes a data set, it may be incapable of generalization even though it fits the training data set very accurately. Over-fitting means getting acceptable prediction by the network for the trained data, but unacceptable prediction for inputs that were not used in the training stage (Hagan et al., 1996). Over-fitting leads to statistically significant, but physically meaningless results. Thus, the network training result should be validated before implementing the application and production mode (Hart, 1999). One good method of validation is the take-one-out approach. One well is excluded at a time from the training stage. In each case the network is trained with the data from the remaining seven wells to predict the measurements from the eighth well (the well that has been excluded from that particular training). This practice is repeated eight times, each time with different as the verification well, where the well logs from the test well are not used in the training.

<table>
<thead>
<tr>
<th>Well</th>
<th>Correlation Coefficient (%)</th>
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<tbody>
<tr>
<td>A01</td>
<td>91</td>
</tr>
<tr>
<td>A03</td>
<td>97</td>
</tr>
<tr>
<td>A09</td>
<td>90</td>
</tr>
<tr>
<td>A15</td>
<td>93</td>
</tr>
<tr>
<td>A17</td>
<td>74</td>
</tr>
<tr>
<td>A18</td>
<td>67</td>
</tr>
<tr>
<td>A20</td>
<td>79</td>
</tr>
<tr>
<td>A21</td>
<td>92</td>
</tr>
</tbody>
</table>

*Table 7.2* The correlation coefficient values at the different well locations. The values range between 67 % and 97 %. The overall correlation coefficient value for all wells is 85 %.
Therefore, the accuracy of the network can be evaluated each time by comparing the predicted result (the testing well is not included in the training) with the actual well data at the excluded well. By taking out Well A09 from the training process, the validation results are shown in Figure 7.7. Appendix 7.B shows the validation result for each case of the eight wells.

*Figure 7.7* The validation of the method is performed by excluding one well (Well A09) from the calculation. The validation result (dark blue curve in A09 panel) shows a close match to the prediction curve using all wells (light blue curve in panel A09).
7.3.5 Porosity and Permeability Mapping

After validating the results, a 2-D mapping of the porosity was generated at the different reservoir levels as shown by Figure 7.8 which indicate that the upper part of the ZOI is more porous than the lower part. The upper part of Subzone 2 (middle) shows the larger spatial spread of the high porosity values among the different levels within the ZOI. Figure 7.9 shows the estimated average porosity for the three subzones within the reservoir. Among the three subzones, Subzone 1 (upper) is the most porous zone followed by Subzone 2 (middle), then Subzone 3 (lower).
Figure 7.8 The regional estimation of porosity at different horizon slices using back-propagation neural network. The upper part of the zone of interest shows higher porosity range than the lower part.
Figure 7.9 The average porosity for the three subzones within the zone of interest.
Relative permeability is one of the most important parameters for reservoir characterization and modelling. Determination of permeability (short for relative permeability) data is required for almost all calculations of fluid flow in petroleum reservoirs. Permeability is defined as “a measure of the ease with which a fluid can flow through a formation”. Interest in permeability information has arisen from the need to solve practical problems in different fields, such as in petroleum engineering, hydrology and geophysics (Narasimhan, 1998). Knowledge of permeability is essential for reservoir development, determining well perforation interval, optimizing stimulation design, and choosing optimal drainage points and production rates.

Permeability data is usually used for estimating ultimate recovery, predicting future reservoir performance, and determining fluid distributions and residual saturation. Therefore, an accurate estimation of permeability is an essential element in the success of the subsurface system management and for 3-D modelling. However, knowledge of permeability is usually obtained directly from core analysis at wells, which is often labour-intensive, costly, and incomplete. Usually, empirical correlations are used to predict relative permeability data. However, obtaining permeability information from empirical relations showed limited success and proved difficult especially for carbonate reservoir rocks. Therefore, an important aim in this chapter is to generate an accurate, spatially heterogeneous field of permeability over the study area by developing an artificial neural network technique (in this case the BPNN).

Permeability usually shows variation both in space (heterogeneity) and in direction (anisotropy) within a geological formation. It is often expressed in units of Darcys. The range of permeability values is extremely wide, varying from less than $10^{-8}$ to over $10^5$ Darcys (Fetter, 1994).
Permeability can be determined by several different methods: core samples, well test analysis, physical models, geostatistical techniques, and artificial neural network approaches. Basheer et al. (1996) used a back-propagation neural network to determine the spatial distribution of permeability in an attempt to delineate the boundaries of a proposed earthen landfill to be constructed at a real site.

In this study, permeability values were estimated using the developed BPNN algorithm. The permeability logs were incomplete for most of the eight boreholes (Figure 7.10); the first four samples (at the top of the ZOI) were missing in most of the wells. The permeability of a sample was estimated from porosity data (that just been estimated), where a training set was compiled using permeability values (from well logs) as desired output and their corresponding porosity values as inputs. Instead of a using simple pairing of a porosity value from a given time level with its corresponding permeability value, the creation of a training set of permeability prediction in this study is more complex and innovative approach. The proposed approach used a set of porosity values to predict a single permeability value. In this study, porosity value of the sample at the current position and the porosity values of four samples above it are used to predict the permeability value at the current position.

Predicted reservoir properties at the well locations and the validation results are shown in Figures (7.10 and 7.11), respectively. Appendix 7.C shows the validation result using take-one-out for each case of the eight wells. These results suggest that the network is generalizing successfully, without experiencing memorization. The error was decreasing as the number of iterations increased which is a characteristic for a well-trained neural network. Another important statistical parameter for analysing the performance of the network is the correlation coefficient between the network’s prediction and the observed values. The artificial network result shows very acceptable agreement
with the well log data. The overall correlation coefficient was 97% in the ZOI (excluding the top four samples). By validating the network using data that were not utilized of the training of the network, the result indicated high degree of accuracy. The regional 2-D mapping of the permeability is shown by Figure 7.12, and Figure 7.13. The former figure shows the 2-D mapping of the permeability for each individual horizon slice; Figure 7.13 shows the 2-D mapping of the average permeability within the three reservoir subzones. The mapping has shown permeability values up to 2500 md; the spatial distribution is mostly showing low-medium values of permeability for each of the twelve time levels. The average permeability of the three subzones of the reservoir indicates that the upper zone (subzone 1) is the most permeable among the three subzones. It also shows that the middle zone (subzone 2) and the lower zone (subzone 3) are least permeable and moderately permeable subzones, respectively.
Figure 7.10  A comparison between the network prediction and the target permeability logs.
Figure 7.11  The validation step for the permeability estimation; Well A01 is excluded.
Figure 7.12  The back-propagation regional estimation of permeability for the different reservoir levels.
Figure 7.13  The spatial distribution of the average permeability for each of the three subzones within the zone of interest.
7.4 CONCLUSIONS

In hydrocarbon exploration, 3-D seismic data play an important role in mapping the spatial distribution of reservoir properties. The relationship between seismic attributes and reservoir properties can provide essential information for modelling and understanding the subsurface. Undoubtedly, porosity and permeability data are considered the most valuable information required in reservoir simulation studies.

A neural network of a multi-layer perceptrons has been created to discover the non-linear relationship between the input data and the target reservoir property. The back-propagation optimization algorithm has been derived and incorporated in the network to assure better prediction accuracy. The BPNN technique provides a valuable tool allowing earth scientists to characterize hydrocarbon reservoirs using integrated seismic and well data, as was demonstrated in the present study of a carbonate reservoir. BPNN is very good at prediction because it can learn from a relatively small set of examples and its generalization ability allows it to make predictions on input data that were never used in its training set.

The overall prediction accuracy for mapping the porosity over the study area by BPNN using four input seismic attributes (instantaneous amplitude, instantaneous phase, instantaneous frequency, and acoustic impedance) was 85%. Next, permeability mapping was produced with by BPNN high accuracy prediction using porosity as an input. The method was validated before mapping the spatial distribution of the reservoir properties.
Here, the BPNN has successfully integrated seismic data with the geological knowledge, predicted the desired properties (porosity and permeability), and helped to define their main spatial boundaries and patterns.
CHAPTER 8 AN INNOVATIVE APPROACH FOR INTRA-WELL LITHOLOGY CLASSIFICATION

“Creativity is thinking up new things. Innovation is doing new things.”
(Theodore Levitt)

**Lithology** identification is one of the key tasks for characterizing a reservoir. The traditional approach in identifying the reservoir lithology is through describing the reservoir cores, but core description is costly, time consuming, and localized at the drilling location. Different geologists may give different lithology description for the same drilled location; thus, the description could be biased.

In comparison to the available traditional methods, a new hybrid approach which combines ‘artificial neural network’ and ‘fuzzy logic’ methods is introduced in this chapter for identifying the reservoir lithofacies at a well location. The proposed system uses the wells main logs innovatively to generate lithofacies classification within the zone of interest.

The technique is implemented at one of the wells within the study area,. The result gives unbiased
8.1 INTRODUCTION

Lithology identification is one of the main tasks for characterizing a reservoir. According to Rider (1996), lithological information can yield important characteristics of a reservoir, such as mineralogy, inferred origin, fossil content, or hydrocarbon accumulation capability. Conventional methods show only limited success in predicting reservoir lithology, especially in carbonate reservoirs (Moline and Bahr, 1995). This is due to the spatially heterogeneous nature of carbonates (Kopaska-Merkel and Mann, 1992).

Analysis of core data is a traditional method for describing the reservoir lithology. However, coring is an expensive and time consuming process, and in most cases cores are incompletely recovered from a well. In addition, core descriptions are usually subjective and can vary widely among geologists, such that the descriptions are subject to a level of bias. Therefore, a new method of generating un-biased reservoir descriptions which is cost-effective in terms of both time and financial cost is proposed and developed in this chapter.

Recent studies have shown that state-of-the-art methods, such as artificial neural networks (ANNs) or fuzzy logic (FL), are at present the leading approaches for more accurate prediction of reservoir properties (including lithology) (Fung et al., 1997). The ANN approach is distinct in its ability to learn by example and then generalize to obtain accurate results, while FL is another promising method that takes into account the interpreter knowledge (linguistic information) in obtaining accurate results.

This chapter develops and implements a hybrid approach that combines ANN and Fuzzy Logic Interface (FI) techniques for an optimal (un-biased / cost-
effective) result. The proposed method is an innovative approach towards unbiased lithology identification achieved through combining the Adaptive Resonance Theory (ART2) artificial neural network cluster and the fuzzy “if-then” rule; this combination should increase the prediction accuracy (Cox, 1998). An additional advantage of the proposed technique is that it can be used to predict the lithology of un-cored wells by utilizing various well log data sources.

8.2 ADAPTIVE RESONANCE THEORY (ART2)

The adaptive resonance theory is a type of ANN that was introduced by Stephen Grossberg in 1976. It was motivated by an analysis of experimental literature in vision, speech, cortical development and reinforcement learning (Grossberg, 1976). There are several different models of the ART family network including ART1, ART2, ART3, Fuzzy ART, ARTMAP, and Fuzzy ARTMAP (Carpenter et al., 1991; Carpenter et al., 1992). The basic ART system is an unsupervised learning model; however, supervised and unsupervised ART networks have been developed (Figure 8.1). The main differences among the different ART networks are briefly described in Table 8.1. The basic ART system has been developed and adapted for many applications (Duda et al., 2001; Levine, 2000). This network was initially motivated by biological studies; it is more common implemented for biological researches. Here I introduce it into geophysical application for clustering the lithology at well locations using logs data.

One of the main features of ART networks is being stable and plastic which makes them efficiently suitable for pattern matching process; the external
pattern input is compared to an internal active cluster (Carpenter, 1997). Appendix 8.A has more information about adaptive resonance theory (ART).

ART2 is a clustering algorithm and a member of the ART family. It is a self-organizing network designed to perform for continuous-valued (analog) input vectors using an unsupervised learning model (Carpenter and Grossberg, 1988).

The ability of a network to learn a new pattern is called ‘plasticity’, and the ability for the new learning not to be affected by the previous learning is called ‘stability’. One important feature of ART2 that is lacking in other networks (such as SOM and BPNN) is its ability to learn important new patterns while still responding to previously learned patterns (Grossberg, 1987). This feature enables the network to overcome the ‘Stability-Plasticity dilemma’ (SPD), so that it can provide predictions beyond the training data sets; this property is valuable, especially for heterogeneous carbonate reservoirs (Grossberg, 1995).

According to Grossberg (1987), ART2 network is plastic (store new input patterns) and stable (protect stored patterns from being erased). ART2, when compared to SOM or BPNN, can incrementally cluster the input data into arbitrary numbers of categories based on the characteristics of input well log signatures. In other words, ART2 is capable of classifying even if the test data are outside the range of the training data (Carpenter and Grossberg, 1987 a and b); therefore, ART2 is considered a better predictor for pattern recognition tasks (Fausett, 1994).
Figure 8.1 The general types of ART networks: unsupervised and supervised. Each type has a different sort of ART networks.
ART Network | Description
--- | ---
ART 1 | Binary input, and simple F1-layer
ART 2 | Analog (continuous) input, and more complex F1-layer
ART 2-A | ART 2 with qualitative results
ART 3 | Builds on ART2 for biological purposes
Fuzzy ART | Implements fuzzy logic into ART’s pattern recognition
ARTMAP | Also known as Predictive ART, combines two slightly modified ART-1 or ART-2 units into a supervised learning structure where the first unit takes the input data and the second unit takes the correct output data, then used to make the minimum possible adjustment of the vigilance parameter in the first unit in order to make the correct classification.
Fuzzy ARTMAP | is merely ARTMAP using fuzzy ART units, resulting in a corresponding increase in efficacy.

Table 8.1 A brief description of the different ART networks.

8.2.1 Architecture

The basic ART2 architecture as suggested by Carpenter and Grossberg, (1987b) is illustrated in Figure 8.2. There are two main layers ($F_1$-layer and $F_2$-layer) and one resetting system (Fausett, 1994). Each of these three components contains a number of neurons. The $F_1$ layer is the input processing field which process the incoming input pattern through different nodes and operations. The $F_2$ is the competitive layer comprising the cluster units where it receives the processed signal from $F_1$ layer then clusters it to one of the clusters in $F_2$ layer. A reset mechanism is incorporated to control the degree of similarity of patterns assigned to the same cluster it uses the vigilance.
parameter \( (\rho) \), which is a measure of similarity, as a match criterion (Kosko, 1997). \( \rho \) is one of the main parameters in the network as defined in Table 8.2.

8.2.1.1 F1 and F2 Layers

The \( F_1 \) and \( F_2 \) layers are fully connected through two major types of weights: **bottom-up weights** \((b_{ij})\) from \( F_1 \) to \( F_2 \), and the **top-down weights** \((t_{ji})\) from \( F_2 \) to \( F_1 \). The weights associated with the bottom-up and top-down connections between \( F_1 \) and \( F_2 \) are called **long-term memory** (LTM) (Freeman and Skapura, 1991). On the other hand, the **short-term memory** (STM) consists of patterns of activity that develop over the nodes in the two layers (Freeman and Skapura, 1991).

Six types of units constitute the \( F_1 \) layer: \( W, X, V, U, P \) and \( Q \). For each of these types, there are \( n \) individual units, where \( n \) is the dimension of an input pattern. \( P \) sends normalized signals to \( F_2 \) via \( b_{ij} \) and receives signals from \( F_2 \) via \( t_{ji} \). Contrast enhancement of the filtered \( F_1 \) to \( F_2 \) input pattern, and reset or enduring inhabitation of active \( F_2 \) nodes are the key properties of \( F_2 \) layer. The units of the \( F_2 \) layer compete in a winner-takes-all mode to learn each input pattern, where learning occurs only if the top-down weight vector for the winning unit is sufficiently similar to the input vector. The \( F_2 \) layer determines the clusters where the input patterns should be placed.

8.2.1.2 Resetting System

\( R \)-module determines the resetting condition. “The resetting system provides control over the degree of similarity between various criteria used” (Freeman and Skapura, 1991).
The vigilance parameter (VP) (represented by $\rho$) is an important parameter in ART2 which acts as threshold value to filter inputs that do not match any stored log facies. VP ranges between zero and one where its value is based on the interpreter’s judgment which is usually set to more than 0.9. This parameter assesses how closely the input should be to the top-down prototype in order for resonance (learning) to occur during the training stage.

The input and stored prototype will resonate when they are sufficiently similar where the input pattern is accepted and the weights ($b_{ij}$ and $t_{ji}$) are updated; notice that update takes place when resonance is established. However, when an input is not similar to any of the stored prototypes, a new cluster is formed.
**Figure 8.2** The architecture of the ART2 network. It consists of two layers ($F_1$-layer and $F_2$-layer), and a reset module (R).
### Parameter Definition

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>n</td>
<td>Number of input units ( $F_1$ layer)</td>
</tr>
<tr>
<td>m</td>
<td>Number of cluster units ( $F_2$ layer)</td>
</tr>
<tr>
<td>a, b</td>
<td>Fixed weights in the $F_1$ layer; sample values are a=10, b=10.</td>
</tr>
<tr>
<td>c</td>
<td>Fixed weight used in testing for reset; a sample value is c=0.1</td>
</tr>
<tr>
<td>d</td>
<td>Activation of winning $F_2$ unit; a sample value is d=0.9</td>
</tr>
<tr>
<td>e</td>
<td>A small parameter introduced to prevent division by zero when the norm of a vector is zero</td>
</tr>
<tr>
<td>$\theta$</td>
<td>Noise suppression parameter; a sample value is $\theta=0.2$</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>Learning rate; a sample value is $\alpha=0.1$</td>
</tr>
<tr>
<td>$\rho$</td>
<td>Vigilance parameter; a sample value is $\rho=0.95$</td>
</tr>
<tr>
<td>$t_{ji}$</td>
<td>Top-down weights</td>
</tr>
<tr>
<td>$b_{ij}$</td>
<td>Bottom-up weights</td>
</tr>
</tbody>
</table>

#### Table 8.2 The main parameters in the ART2 network.

### 8.2.2 Algorithm

#### 8.2.2.1 Main Calculations

The following Equations are the main operations (activations) that take place within the nodes of the $F_1$ layer

$$u_i = \frac{v_i}{e + \|v\|}, \quad \text{................................. (8.1)}$$
\[ w_i = s_i + au_i, \] ................................. (8.2)

\[ p_i = u_i + dt j_i, \] ................................. (8.3)

\[ x_i = \frac{w_i}{e + \|W\|}, \] ................................. (8.4)

\[ q_i = \frac{p_i}{e + \|P\|}, \] ................................. (8.5)

\[ v_i = f(x_i) + bf(q_i). \] ................................. (8.6)

The activation function used in the algorithm is:

\[
f(x) \begin{cases} x & \text{if } x \geq \theta \\ 0 & \text{if } x < \theta \end{cases} \] ................................. (8.7)

8.2.2.2 Main Steps

The following steps are summarized from Fausett (1994):

Step 0. Initialize parameters \(a, b, \theta, c, d, e, \alpha, \rho\).

Step 1. While stopping condition is false, do Steps 2-12.

(Perform the specified number of epochs of training.)

Step 2. For each input vector \(s\), do Steps 3-11.

Step 3. \(F_1\) unit activations:

\[ u_i = 0, \quad x_i = \frac{s_i}{e + \|S\|}, \]

\[ w_i = s_i, \quad q_i = 0, \]

\[ p_i = 0, \quad v_i = f(x_i). \]

Update \(F_1\) unit activations again:
\[ u_i = \frac{v_i}{e + \|V\|}, \]
\[ w_i = s_i + au_i, \]
\[ p_i = u_i, \]
\[ x_i = \frac{w_i}{e + \|W\|}, \]
\[ q_i = \frac{p_i}{e + \|P\|}, \]
\[ v_i = f(x_i) + bf(q_i). \]

Step 4. Compute signals to \( F_2 \) units:
\[ y_i = \sum_i b_{ij} p_i. \] \hspace{1cm} (8.8)

Step 5. While reset is true, do Steps 6-7.

Step 6. find \( F_2 \) unit \( Y_j \) with largest signal. (define \( J \) such that
\[ y'J = y_j \text{ for } j=1,\ldots, m. \])

Step 7. Check for reset:
\[ u_i = \frac{v_i}{e + \|V\|}, \]
\[ p_i = u_i + dt \cdot f_i, \]
\[ r_i = \frac{u_i + cp_i}{e + \|U\| + c\|P\|}. \]

If \( \|r\| < \rho - e \), then
\[ y'J = -1 \text{ inhibit (J)} \]
(reset is true; repeat Step 5);

If \( \|r\| \geq \rho - e \), then

\[ w_i = s_i + au_i, \]

\[ x_i = \frac{w_i}{e + \|W\|}, \]

\[ q_i = \frac{p_i}{e + \|P\|}, \]

\[ v_i = f(x_i) + bf(q_i). \]

Reset is false; proceed to Step 8.

Step 8. Do Steps 9-11 (number of iterations) times.
(Perform the specified number of learning iterations.)

Step 9. Update weights for winning unit J:

\[ t_{Ji} = \alpha du_i + \{1 + \alpha d(d - 1)\} t_{Ji}, \quad \ldots \quad (8.9) \]

\[ b_{iJ} = \alpha du_i + \{1 + \alpha d(d - 1)\} b_{iJ}. \quad \ldots \quad (8.10) \]

Step 10. Update \( F_1 \) activations:

\[ u_i = \frac{v_i}{e + \|V\|}, \]

\[ w_i = s_i + au_i, \]

\[ p_i = u_i + dt_{Ji}, \]

\[ x_i = \frac{w_i}{e + \|W\|}, \]

\[ q_i = \frac{p_i}{e + \|P\|}, \]

\[ v_i = f(x_i) + bf(q_i). \]
Step 11. Test stopping condition for weight updates.
Step 12. Test stopping condition for number of epochs.

A summary of the algorithm in text description (format) is attached in Appendix 8.B.

8.3 IMPLEMENTATION

“The self-stabilizing property makes ART2 an attractive candidate for application to real-world problems” (Caudell et al., 1994). ART2 has been implemented in several different disciplines, such as pattern recognition (Whiteley et al., 1996), civil engineering (Faghri and Hua, 1995), and environmental science (Xie et al., 1994). This Chapter develops the ART2 algorithm, then proposes an innovative approach to classify the lithology of the carbonate reservoir at one of the well locations (Well A20).

Four types of well logs at Well A20 were used to estimate the lithology: sonic (DT), gamma ray (GR), neutron-porosity (NPHI), and density (RHOB) logs (Figure 8.3). These four log types are ones of most related to lithology. Values of parameters in each log can be classified into distinct lithologies (Table 8.3). The statistical data and histograms for the input logs are shown in Figure 8.4.

Usually, when drilling a well, logging and coring are run to obtain more information about the reservoir. The best traditional way to obtain the reservoir lithology is through coring which usually takes place after logging the reservoir. However, because coring is a costly process, decision can be taken sometimes to run only logging (no coring) and infer the lithology from correlating the different log types which gives an estimate of the lithology.
However, core description and logs interpretation can generate biased outcome caused by using different describers or interpreters.

Here, I propose, as an alternative way to logs correlation approach, an innovative strategy for classifying wells lithology using hybrid-system which combines ART2 with a fuzzy interface to obtain more accurate result (Figure 8.5).

<table>
<thead>
<tr>
<th>Well Logs</th>
<th>Symbol</th>
<th>Unit</th>
<th>Sandstone</th>
<th>Limestone</th>
<th>Dolomite</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sonic</td>
<td>DT</td>
<td>$(\mu s/ft^2)$</td>
<td>53 - 100</td>
<td>47.6 - 53</td>
<td>38.5 - 45</td>
</tr>
<tr>
<td>Density</td>
<td>RHOB</td>
<td>$(g/cm^3)$</td>
<td>2.59 - 2.84</td>
<td>2.66 - 2.74</td>
<td>2.8 - 299</td>
</tr>
<tr>
<td>Neutron-Porosity</td>
<td>NPHI</td>
<td>(%)</td>
<td>0 - 45</td>
<td>0 - 30</td>
<td>0 - 30</td>
</tr>
</tbody>
</table>

**Table 8.3** Different log parameter values corresponding to different types of lithology (sandstone, limestone, and dolomite).
Figure 8.3 The input logs. From left to right: sonic, gamma ray, neutron-porosity, and density. The y-axis is depth in meters.
Figure 8.4 The histograms for the input logs. From top to bottom: sonic, gamma ray, neutron-porosity, and density.
Figure 8.5 The lithology classification result of the developed ART2 at Well A20. At each depth sample within the zone of interest, the lithofacies is classified into one of four types: wackestone, packstone, grainstone, and mudstone which correspond to 1(red), 2(green), 3(blue), and 4(purple), respectively.
8.3.1 Proposed Networks System

The proposed system is considered ‘hybrid’ because it runs both artificial neural network and fuzzy interface (Figure 8.6). A fuzzy “if-then” rule is used for final decision making by honoring the linguistic knowledge about the reservoir or the depositional system in the area.

A different perspective of characterizing a reservoir and enhancing its analysis suggests combining different types of information sources (Benediktsson et al., 1990; Serpico and Roli, 1995).

The innovation of the proposed system rises from introducing a different type of source information (raw and categorical) then combining the ART2 results through a fuzzy interface yielding to more accurate result.

The raw data uses a normalized input logs values. The categorical data is generated by categorizing each log into five equally spaced zones (categories) starting from the log minimum value and ending at the log maximum value. The categorical input is used to emphasize the important features in the corresponding categories rather than the actual values.

To artificially combine different information types using ART2, different ART2 networks are formed based on these information types: R-ART2 and C-ART2.

Based on the geological knowledge of the reservoir rock in the field, several fuzzy rules are extracted and listed in a prioritized order (Table 8.4).
Figure 8.6 A flow chart showing the proposed innovative system for classifying the lithology. The system runs two separate ART2 networks then combined their results using a fuzzy interface to finally obtain the lithofacies type.
8.3.2 Results

The importance of this technique lies in its ability to predict the lithofacies even for wells that have not been cored, without/before the need to core the reservoir. It is therefore useful for predicting the reservoir properties of missing cores in partially cored wells, and in this manner contributes to characterizing the reservoir: in particular by completing the missing lithological information in the simulation model.

Utilizing the different information types thereby improves the overall accuracy. The raw logs have been categorized to generate a different input type to the system (Figure 8.7).

Using the normalized values of the well logs for one of the wells (A-20) as an input, the R-ART network has revealed informative lithofacies details. Introducing the same input; however, in a different way to the network generated a similar result by C-ART2. Each of the input well logs in C-ART2 network was equally split into five categories (from 1 to 5). The categorized values were used, instead of the normalized values, in the C-ART2 network. Both networks, R-ART2 and C-ART2, showed similar lithofacies classification in the middle zone. The C-ART2 indicates more grainy contents in the upper and lower zones than the result by R-ART2. The results of each network (R-ART2 and C-ART2) are combined through prioritized fuzzy rules (Table 8.4). The prioritized list of lithofacies has been suggested to fulfill the most likely occurrence of the carbonate facies within a reservoir rock. Among the different four lithofacies, wackestone represents the reservoir best quality (higher porosity values). The network will not execute a rule if it has been satisfied by a previous rule. For example, Rules 3 and 4 will not be checked by the network if Rule 1 has been satisfied. Figure 8.8 (a and b) shows the lithology
classification results (in two different displays) for the developed ART2 (titled: R-ART2 and C-ART2), and the proposed system (titled: FINAL). The final result indicates that upper zone (subzone 1) and lower zone (subzone 3) are dominated by grainstone and mudstone, respectively. On the other hand, the middle zone (subzone 2) shows to be enriched with wackestone and packstone.

**Figure 8.7** The categorical classes of the different logs (from left to right): sonic, gamma ray, neutron-porosity, and density. The x-axis is the classification number (from 1 to 5); the y-axis is the depth in meters.
<table>
<thead>
<tr>
<th>Rule</th>
<th>If</th>
<th>Then, final lithofacies is</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>R-cluster or C-cluster contains 'wackestone',</td>
<td>wackestone.</td>
</tr>
<tr>
<td>2</td>
<td>R-cluster contains 'packstone', or C-cluster contains 'packstone',</td>
<td>packstone.</td>
</tr>
<tr>
<td>3</td>
<td>Rule 1 is not satisfied, and C-cluster contains 'grainstone'</td>
<td>grainstone.</td>
</tr>
<tr>
<td>4</td>
<td>Rule 1 and rule 2 are not satisfied, and R-cluster contains 'mudstone', or C-cluster contains 'mudstone', or</td>
<td>mudstone.</td>
</tr>
</tbody>
</table>

Table 8.4 The ‘if-then’ rule (fuzzy interface) which is incorporated into the proposed system for the final lithology classification type.
Figure 8.8  The final lithology classification results. The first and second columns are the classification results which were obtained from R-ART2 (Raw normalized input) and C-ART2 (Categorical input), respectively. The final column (third) is the final lithology classification as has been obtained by the proposed system. (a) The results are shown in a ‘Colored’ form; (b) the results are shown in a ‘Categorized’ form.
8.4 CONCLUSIONS

In this chapter, I proposed an innovative implementation of ART2 for intra-well lithology prediction. To provide different perspective in estimating the reservoir lithology and to enhance the accuracy of the result at the selected well location (Well-A20), the network used four well logs in two types of input forms (raw and categorical). Also, a fuzzy interface was combined with the artificial network through a hybrid system to make the final decision on the lithology. The results obtained in this chapter indicated the potential of using ART2 network for classification and feature recognition tasks. Featured with its ability to classify and recognize features, as well as, its performance efficiency, the result indicated grainy and muddy dominated zones in the upper and lower parts of the reservoir, respectively. The middle zone is estimated to be a combination of packstone and wackestone dominance.

In conclusions, this proposed approach is efficient in classifying the main lithofacies of a well using its log data. The proposed approach is an important tool for identifying the different types of lithofacies especially for complex geological setting which can occur in carbonate reservoirs. The proposed approach is innovative in the way it was structured where the accuracy of result was emphasized and improved through the use of multiple ART2 networks instead of a single artificial network.
CHAPTER 9  CONCLUSIONS AND RECOMMENDATIONS

“To succeed, jump as quickly at opportunities as you do at conclusions.”

(Benjamin Franklin)

This study investigated recent advances of computational and interpretational algorithms in developing an accurate prediction of reservoir properties that can be useful for reservoir modelling. 3-D seismic data has played a role factor in the analysis and understanding of the carbonate reservoir characteristics. 3-D seismic data and well logs for eight wells within the study area were the original data sets to start with in achieving the main aim which is to integrate the 3-D seismic data, and petrophysical well logs for better understanding of the spatial distribution of the reservoir’s main properties. Different reservoir properties and elastic parameters were mapped regionally over the 3-D study area at the different reservoir levels. Porosity, lithology, and permeability which are considered the most important properties in any reservoir study were the main focus in this study.

The original data sets were used in the pre-analysis stage leading to the calculation of the main four seismic attributes that were used as input to the investigated techniques in analysis stage. The pre-analysis phase which also included ‘data quality control (QC)’, ‘seismic data flattening’, and ‘data sets calibration’ has contributed significantly in the consistency in reasonable (direct) correlations (when applicable) for the different analysis approaches that were implemented in this thesis.
The flattening of the seismic data on the top of the reservoir seismic-pick gave more confidence in the result (reservoir properties mapping) and made it easier to implement the techniques and analysis their outcomes.  
The overall correlation for the synthetic generation in the calibration step was 70%. The aim for better understanding and accurate characterizing of the reservoir, clustering and prediction tasks of the reservoir main properties were developed through five main techniques.
9.1. IMPLEMENTED METHODOLOGIES

This study presents state-of-the-art techniques that showed effectiveness in characterizing and understanding the reservoir under study.

9.1.1 Multiple Linear Regression

3-D volumes of different reservoir properties were calculated more accurately by incorporating hierarchical cluster information. More accurate estimation of the porosity was obtained using the improved implementation; it has raised the estimation accuracy by 45% (from 54.6% to 79%). Figure (9.1) shows the improved correlation coefficient between the porosity logs and the predicted porosity for each of the well locations.
Figure 9.1  The improved implementation of the MLR technique has increased the accuracy for estimating the porosity at the well locations.

9.1.2 Grey System Theory (GST)

With the purpose of obtaining the unknown information of the reservoir from its known information, this study has also proposed the ‘grey attribute’ to highlight the reservoir hydrocarbons through the implementation of GST. The result indicated very good correlation between the wells production and the proposed grey attribute. The proposed technique can be considered a new tool for indicating hydrocarbon accumulation that can be useful for studying reservoirs. Having said that, I think more testing should be done using different data.
9.1.3 Kohonen Self-Organising Map (KSOM)

A network that is capable of using either a single input or multiple inputs was developed to cluster the reservoir. The KSOM method has helped to handle the high-dimensional input data and visualize the result into 2-D dimension. It has been very informative method for showing the distribution of the main lithofacies of the ZOI. Based on internal structure of the data, the developed KSOM algorithm revealed general trends within the study area that could be a representation of the lithology spatial spread. The clustering results of the single and multiple fed-input showed similar lithofacies distribution and trending.

9.1.4 Back-Propagation Artificial Neural Network (BP-ANN)

Porosity and permeability, which considered ones of the most important reservoir properties, have been calculated using the developed BPNN. The porosity was estimated first, then it was used to estimate the permeability. The network has generated accurate estimation, giving the resulting correlation coefficients at the well locations (Figure 9.2). The network has shown good generalization through validating the result. The result was validated by take-one-out (taking out one well at a time from the analysis) with an overall correlation-after-validation of 58% (Figure 9.3).
Figure 9.2 The resulting correlation coefficients of BPNN at well locations for estimating the porosity.
Figure 9.3 The correlation coefficient of the validation process for each of the wells (as the well is taken out and using the other seven wells).

9.1.5 Adaptive Resonance Theory (ART2)

ART2 has been implemented for identifying lithology at well locations. The method is proposed to save time and money for analysing the subsurface when drilling wells and after obtaining the necessary logs. Due to the lack of core data, the accuracy of the result needs to be validated.

9.2. RESERVOIR PARAMETERS

Different reservoir properties and elastic moduli have been mapped: (density,
velocities, Poisson ratio, Vp/Vs ratio, porosity, lithology, and permeability). The former three properties are the main focus in this study.

9.2.1 Porosity

The correlation between the real porosity and the estimated porosity has ranged between 59% to 91% using the improved MLR Method. On the other hand, the correlation has ranged from 67% to 97% for the eight wells using the BPNN method. The comparison between the two methods for estimating the porosity indicates that both methods have estimated porosity with good accuracy. BPNN method showed better prediction than the MLR method with an overall correlation of 85% (Figure 9.4). The result also indicates that the MLR, in general, over-estimates the porosity in subzone 2.
9.2.2 Lithology

Analysis of the data indicates that the lower half of the ZOI is mud-abundant. In general, the lithology of the ZOI has been inferred through clustering tasks (KSOM and ART2). The inter-well analysis of KSOM has clustered the ZOI into nine carbonate lithofacies. Furthermore, the intra-well analysis at Well A20 has indicated that subzones 1 and 3 are dominated by packstone (grainy, and muddy, respectively) and that subzone 2 is mostly wackestone with some grainstone concentrated at the top.

Figure 9.4 A comparison between MLR and BPNN estimation of porosity.
9.2.3 Permeability

The permeability was estimated at well locations and mapped regionally over the study area using the BPNN approach and porosity input. The overall correlation coefficient between the permeability log and the estimated permeability was above 90%. The mapping result showed general trends and indicated some highly permeable localities.

9.3. RESERVOIR MAIN ZONES

The study identified three main subzones within the zone of interest (ZOI): Zone 1, Zone 2, and Zone 3. This study indicates that each of these subzones has its own characteristics.

9.3.1 Subzone 1

Subzone 1 is interpreted as mostly of an evaporite sealing layer with higher occurring chance of high-energy shallow depositional environment deposits such as grainstone, packstone and shoal.

9.3.2 Subzone 2

Subzone 2 is interpreted as the main hydrocarbon producing carbonate facies of shelf deposits. The upper part of this subzone (slices 936 ms and 940 ms) showed to be the main contributors to the high porosity values in this zone; it is
interpreted as most likely to be coral facies of the intra-shelf region that deposited as sheets.

9.3.3 Subzone 3

In general this Subzone (3) shows the lowest average porosity. It indicates the dominance of low energy deposits that usually occur in the outer ramp of deep marine environment represented by the mudstone and wackestone facies, which are common facies in ramps.

In summary, the main reservoir properties (density, porosity, permeability, and lithology) were estimated and can be used to better understand and characterize the reservoir. One of the potential applications of this study can be for reservoir simulation and to come up with a 3-D reservoir model.

9.4. CHALLENGES

There have been many challenges that had been faced with in this study, including the following:

1) Over-fitting:
Validation of the result was carried by taking-one-well-out at a time which gives a measure of the technique performance. One concluding remark is that the correlation coefficient is ranging for the different wells indicating that the memorization was avoided.
2) Network parameters selection:
Depending on the investigated techniques there are a number of essential parameters that needs to be set selectively after many trials and errors, for example, the size of the SOM map, and the learning rate

3) Random weight initialization:
One of the factors is also the initialization of random weights which is one of the main built-in steps within the most of the artificial networks algorithm. For example, the SOM starts with initializing the weight matrix which must be saved and used in the parameter selection process (for example, when testing the size of the SOM map)

4) Scope and limitation of data:
Sometimes, one or few wells showed humble performance which can be accounted to different reasons including: 1) that the test data is not in the range of the training data either to shortage in wells data, and / or 2) due to the large size in the study area.

5) In addition, the proposed hybrid system (ART2s and fuzzy interface) for predicting the intra-well lithology should be further tested/validated by obtaining the core data to check the prediction accuracy. Also, the classification by the proposed method should be checked at couple of other well locations to ensure that the method is capturing the different classification of the heterogeneous reservoir. Different types of input logs can also be tested.
9.5 RECOMMENDATIONS AND FUTURE WORK

The following points are recommended for further investigation in the future:

1) Due to the data limitation, this study was carried using only eight wells with basic types of logs. Therefore, it is recommended to investigate the performance of the proposed techniques by incorporating core data, as well as, by using more numbers of wells and logs.

1A) One important point is to obtain core data and incorporate it in the analysis when applicable. The fact that core data was missing to validate the result of the last innovative technique (multiple ART2s), and that depth logs were used to give more space of testing the functionality and the accuracy of the model, the idea of using time-calibrated reservoir properties as the input which leads to direct advantage for its usage in 3-D seismic data where lithology of the reservoir can be classified for the whole cube, even though, the number of samples will be reduced (in time domain compared to depth domain) noticeably.

1B) Another important point is to increase the number of wells, or / and use different types of logs. This leads to increasing the number of trained vectors that will contribute efficiently utilize the techniques to reflect/represent the heterogeneity of the reservoir.

2) Other area of research studies such as pore scale modelling from core image can be incorporated with ANN model to improve the accuracy of prediction.

3) Investigate other types of advanced soft computing techniques that can have influential applicability to increase the understanding and improve the characterization of reservoirs, especially, carbonate. During my research, I
came across very interesting techniques which seemed very promising, therefore, worth future investigation such as Support Vector Machine (SVM), Fuzzy Logic (FL), and other types of neural network such as genetic and functional networks.

* One of the recent machine learning and data mining algorithms is the SVM which is based on statistical learning theory that adheres to the principle of structural risk minimization of an upper bound of a generalization error rather than minimizing the training error. It has been considered as a robust tool for prediction and classification tasks. Literature indicates that SVM technique is developing in many scientific fields including seismic exploration. One of my interests is to develop this technique to help for better characterization and understanding of reservoirs with more emphasis on carbonate.

* Another interesting subject is the fuzzy logic which is an extension of the classical logic (where every value is either true or false). Fuzzy logic incorporates the user knowledge into the analysis of reservoir studies based on fuzzy set theory using membership function that uses degrees of trueness and falseness. The approach can be useful, for example, for classifying the reservoir lithofacies by identifying different sets of fuzzy rules which can be utilized in a fuzzy partitioning system.

* Research studies on genetic neural network showed promising results for predicting reservoir properties. Le and Potter (2003) and have showed how to predict the permeability from un-cored wells using this type of artificial networks. This approach tends to divide the reservoir into several hydraulic units on the basis of the geophysical and geological properties. A hydraulic unit is defined as “a representative unit within which the petrophysical and geological properties are consistent and having similar effect on fluid flow” (Jude et al., 1993). The properties along these representative genetic units
(RGU) can be trained and tested along the reservoir; this makes this approach useful when limited data are available for training the network.

In conclusion, five state-of-the-art analysis techniques have been presented in this thesis. The developed algorithms have been implemented on the Arab-D carbonate reservoir within a 3-D study area in Saudi Arabia. The validation of the results has proved these techniques to be powerful in their capabilities in characterising the reservoir of a 3-D post-stack seismic data. The developed methodologies should work properly for other 3-D post-stack seismic data given that the pre-analysis stage has been preformed.

The data analysis in this study has revealed some useful information about the target reservoir within the study area. For example, one of the important information that has been learnt about the ZOI is that it consists of at least three main subzones; analysing each subzone separately had generated better prediction accuracy for the reservoir properties. These approaches have offered different important regional (spatial distribution) mappings not only contribute to unveil some ambiguities about the reservoir heterogeneity, but also can improve/update the 3-D simulation models.
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APPENDICES

APPENDIX 1.A

ARTIFICIAL NEURAL NETWORKS

When 3-D seismic data are available, the artificial neural networks (ANN) approach is distinct from other conventional approaches in terms of its classification and prediction capability. Here, ANN methods (both supervised and unsupervised) are investigated for the purpose of characterizing the carbonate reservoir. Three out of five proposed techniques in this thesis are based on ANNs, and this appendix is devoted to a review of literature on ANNs.

1A.1 Introduction

The Artificial Neural Network (ANN) is considered as one of the essential components of an artificial intelligence (AI) system. Artificial intelligence, also known as soft computing (SC), is a broad umbrella that includes ANNs as well as covering a variety of other interesting fields such as, Support Vector Machines (SVM), Fuzzy Logic (FL), evolutionary and Genetic Algorithms (GA), swarm intelligence models, robotics, and expert systems.

Unlike ‘hard computing’ where strict logic is used to achieve a definitive and precise answer, soft computing addresses several characteristics of uncertainty in the data.
Soft computing has been identified in literature by several different authors. Kecman (2001) refers to soft computing methods as “universal approximators of any multivariate function of particular interest for modeling highly non-linear, unknown, or partially known complex systems, plants, or processes.”

Soft computing is the branch of computer science concerned with making computers behave like humans. The term was first employed by John McCarthy at the Massachusetts Institute of Technology (MIT) in 1956. The aim of AI/SC has been defined by Sage (1990) as the development of paradigms or algorithms that require machines to perform tasks that apparently require cognition when performed by humans. This definition has since been widely broadened to include preceptrons, language and problem solving, as well as, conscious and unconscious processes (Memmi, 1989; Bishop, 1996).

1A.2 ARTIFICIAL NEURAL NETWORK (ANN) AND NEURAL COMPUTING

Artificial neural networks have advanced conventional techniques by many advantages including: the ability to address either continuous or categorical as either inputs or outputs, independence from assumptions about the distribution of input or output variables, and the ability to address non-linear relationships. Without the need for a priori statistical analysis or mathematical model selection, an ANN is able to discover the relationship between the input data and the desired output by employing a set of non-linear and/or linear activation functions. Its power lies in the fact that it learns and understand this relationship instead of fitting a curve or modelling a data. This training/learning ability allows it to work for data beyond those used in the learning process; given a set of input and target measurements (in the present case, the well data), an ANN can learn and extract complex non-linear relationships within
the data. These relationships can be applied to estimate the target variables when direct measurements are not available. An ANN’s ability to learn and generalize gives the ANN an advantage over conventional approaches, and overall an ANN has fewer drawbacks than other methods (Wiener, 1995). It has been shown that a careful neural network analysis is capable of providing more accurate and repeatable results when compared with previously used methods (Mohaghegh et al., 1995).

The literature contains many published papers which provide useful introductions to the ANN field; some of the key references are listed below.

One of the classical introductory papers was written by Lippmann (1987). The paper reviews six ANN models for pattern classification. More recent introductions to neural computing and ANNs can also be found in Beale and Jackson (1990), Eberhart and Dobbins (1990) and Simpson (1990a; 1990b). Historical and theoretical aspects of selected neural network models can be found in the 1990 IEEE proceedings (Widrow and Lehr, 1990). Cowan and Sharp (1988) discussed neural networks from the biological perspective. Finally, several mapping algorithms were developed between the 1970s and early 1980s: for example Takeuchi and Amari 1979; Whitelaw and Colvan 1981; Grossberg 1976; Malsburg 1973; Kohonen 1982b; Kohonen 1982a; Willshaw and von der Malsburg 1976.
1A.3 FUNDAMENTALS

1A.3.1 Historical Background

According to Anderson and Rosenfeld (1988), the roots of the ANN method dates back to 1890, and can be attributed to a study by William James (1890).

William James was pioneered research on the structure and functions of the brain. Originally, analytic neural modelling was typically connected with psychological theories and neuropsychological research. McCulloch and Pitts are considered to be the first theorists to conceive the fundamentals of neural computing (Kohonen, 1988), and tried to model the low-level structure of a biological brain system (McCulloch, 1943).

They used a massively parallel architecture and proved that a logical expression can be represented by networks consisting of neurons. Their work is considered to be the starting point for the development of learning network models (Eberhart and Dobbins, 1990).

Donald Hebb (1949) published a book entitled ‘The Organization of Behavior’, which was a source of inspiration for researchers developing computational models of learning and adaptive systems. He focused mainly on an explicit statement of a physiological learning rules for synaptic modification. Hebb was the first to identify a method for updating the synaptic weights, known as Hebbian learning, which is still implemented in today’s artificial neural networks (Hebb, 1949). Also, he proposed that the connectivity of the brain is continually changing as an organism learns differing functional tasks, and that the neural assemblies are created by such changes.
Ashby’s (1952) book ‘Design for a Brain; the Origin of Adaptive Behavior’ proposes that the adaptive behavior is learned rather than instinctive. The dynamic aspects of the living organism as a machine and the related concepts of stability are also emphasized in Ashby’s book.

The idea of non-linear adaptive filters was proposed by Gabor (1954), who suggested that learning is accomplished in these filters by feeding samples of a stochastic process into the machine, together with the target function that the machine was expected to produce. In 1954, Farley and Clark (1954) introduced adaptive stimulus-response models, which were then further elaborated by Rosenblatt (1958), Caianiello (1961), and Steinbuch (1961). The **perceptron artificial neural network** was first defined by Rosenblatt and lays the foundations for both supervised and unsupervised training algorithms that are currently used in today’s implementations in both the multi-layer perceptron and Kohonen networks.


Widrow and Hoff (1960) introduced ADALINE, which is one of the most important ANNs. It is similar to the perceptron ANN; however, with a learning algorithm, the least mean squares algorithm, that is used today in multilayer perceptron networks.

A major development in ANNs was achieved following publication of the book entitled ‘Perceptrons’ by Minsky and Papert in 1969. Progress then slowed in the 1970s, but major milestones were still reached. For example, an electrical engineer, Teuvo Kohonen, published a work on associative memory (Kohonen,
1972), simultaneously yet independently to similar work by James Anderson (1972) who, by contrast, has a neurophysiology background. Both works provided foundations for the unsupervised learning neural networks introduced in 1982 by Kohonen (1982a; 1982b) with his first publication on the Kohonen Self-Organizing Map (SOM).

Stephen Grossberg is considered as one of the most prominent and controversial researchers in the field of neural networks, because his interest was more focused on the physiological plausibility aspect of network structures rather than the usefulness of their engineering and science applications. Together with his spouse, Gail Carpenter, they developed one of the most complex networks, which is known as the Adaptive Resonance Theory (ART), that can learn without supervised training through simple mathematical expressions (Grossberg, 1973; Grossberg, 1982; Grossberg, 1988; Gevins and Morgan, 1988; Caudill, 1988).

A new visual pattern recognition type of network, NEOCOGNITION, that was originally described by Fukushima, appeared towards the end of 1970s (Fukushima, 1980; Fukushima, 1982). The NEOCOGNITRON network assumes that not only the desired response is known, but also that the computational process right through the network is also known, which makes the network useful for a few applications. John Hopfield published two key papers (Hopfield, 1982; 1984), which significantly boosted ANN development. His new ideas showed that the structures of ANNs can be generalized to give high degree of robustness. Even though the networks are mathematically easily to analyse, they have two limitations which restrict their application: “they can only store about 15% as many states as the network has neurons and the binary patterns stored must be chosen so that their respective Hamming distances are about 50% of the number of neurons” (Hopfield, 1982; Hopfield, 1984). One of the important practical implementations of the so-called ‘Hopfield theory’ was
silicon chip ANN hardware, which was announced by AT&T in 1986. Some of the most popular published volumes on the resulting Parallel Distributed Processing (PDP) are Rumelhart and McClelland (1986, Volumes 1 and 2) and Maloney (1989), which cover the practical issues associated with different ANNs. This work led to the development of the back-propagation neural network (BPNN) algorithm, after a publication in Nature (Rumelhart et al, 1986), and was developed simultaneously and independently by Parker (1985) and even earlier by Werbos (1974). Some of the advantages of this popular algorithm are that it overcomes the limitations inherent in both the Hopfield and Boltzmann approaches.

Research and interest in ANN theory and applications has boomed since 1987. Many journals are now dedicated to ANN research, for example Neural Computation by MIT Press, the Neural Networks Journal (NNJ) of the International Neural Networks Society (INNS) and the IEEE Transactions on Neural Networks.

1A.3.2 Definition

Many definitions can be found in the literature for an ANN system. Broadly, an ANN is an information-processing system that has certain performance characteristics in common with biological neural networks. Generally, there are two aspects in which ANN resembles the brain: knowledge is acquired by the network through a learning process, and the interneuron connection strengths known as synaptic weights are used to store the knowledge (Haykin, 1999). In general, an ANN is a machine that is designed to model the way in which the brain performs a particular task or function of interest. Studies indicate that the brain has an associative property and self
organising capabilities which include the following tasks: association, categorisation, generalisation, classification, feature extraction and optimisation. These brain tasks can also be performed by the neural network models (Vemuri, 1988). An ANN is “a biologically-inspired computing methodology which tries to mimic the learning method used in a human brain”, and in practice are based on very simplified brain-like information encoding and processing models, comprising a type of massively parallel computing architecture. Alexander and Morton (1990) have adopted the following commonly accepted definition: “A neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use”.

1A.3.3 Biological and Artificial Systems

The basic building blocks of the nervous system are nerve cells called neurons. A schematic representation of the biologic nerve cell is shown in Figure 1A.1. The biological neuron consists of three main parts: dendrites, a cell body (soma), and an axon. A dendrite is a finely structured part that receives signals from other neurons and carries them to the cell body of the parent neuron. The cell body receives, integrates and compares signals from dendrites with a threshold before sending an output signal. Depending on the nature of the input signal, the neuron activates in either an excitatory or inhibitory fashion (Faussett, 1994). An axon is a long, thinly-stranded part of the neuron which splits into thousands of branches to send out signals generated by the cell body. At the end of each branch of an axon, a synapse transmits the signal into other neurons.

By changing the effectiveness of individual synapses, so that the influence of one neuron on another changes, learning takes place. Through learning, the
numbers of neurons and synapses are expected to increase over time. It is estimated that the human brain contains on the order of 10 to 500 billion neurons (Rumelhart et al, 1986). Meanwhile, Shepherd and Koch (1990) estimated that the numbers of neurons and synapses in the human brain are 10 billion and 60 trillion, respectively.

Each neuron connects to hundreds to thousands of other neurons. This architecture is the main driving force behind the complex behaviour that comes to us naturally, such as catching or monitoring an object. On the other hand, these natural and simple tasks require many complex calculations that sophisticated computers are unable to perform, but that humans can do routinely and instinctively.

Another interesting fact is that the cycle time of neurons in the human brain is approximately 10 to 100 milliseconds, but only nanoseconds for a computer chip. The neuron speed is thus estimated to be five to six orders of magnitude slower than the silicon logic gate, but the brain compensates for this shortcoming through the massive interconnection between neurons.

According to Freeman and Skapura (1992), a typical mathematical neuron of an ANN is much simpler than the biological neuron (Figure 1A.2). ANNs were inspired by biological neural networks. An ANN is modelled as having similar main components to that of the biological networks found in the brain and nervous system. Therefore, ANNs are computational models inspired by brain structure, mechanism and functions (Golden, 1996).
**Figure 1A.1.** A schematic representation of biologic nerve cell.
Figure 1A.2. A simplified artificial neuron.

Processing Elements (PE), also called ‘neurons’ or ‘nodes’, and their interconnections (synapses) are the main constituents of ANNs. First, a PE which has many inputs but only one output becomes an input to other PEs. The output of each PE is determined by a non-linear function (activation function) of the PE's inputs and relies only on its inputs, so it responds to local rather than global information. Second, interconnections between PEs are weighted to determine the strength of each interconnection. Some networks use fixed weights, while in other uses the weights are modified.
Weight modification is performed according to some specific learning law which is the key to the ability of PEs to exhibit learning and memory.

6.3.4 Network Learning

Learning in biological neural networks involves adjustments to the synaptic connections that exist among neurons; this is also true for the ANN. As mentioned earlier, the ANN is trained by presenting several input patterns, so that the network must learn according to a learning rule.

A learning rule refers to a procedure or an algorithm which adjusts the weights in order for the ANN to perform a desired task. Just like humans, an ANN can learn either by an example or by themselves (Bolt et al., 1997). The way an ANN learns is often used to classify the ANN type.

Based on the learning type, ANNs can be categorized into two types: ‘supervised’ and ‘unsupervised’ networks.

Supervised learning networks are trained to perform a task by repeatedly presenting examples of the input which the networks receive, paired with the known desired output. By definition, a supervised ANN uses a training data set for which both the input data and target output are known/provided. The network utilizes the target as a teacher/guider to ensure that the network is performing correctly.

The training algorithm adapts the weights in the network by using the difference between the real outputs and the desired outputs. By iteratively adjusting connection weights and reducing model errors, the supervision process defines relationships between the input and output data. This type of networks is best for prediction and classification tasks. The back-propagation neural network is well known as one of the widely used algorithms in the supervised category. Figure 1A.3 illustrates the supervised learning process.
Unsupervised learning schemes do not require knowledge of the desired output (target) in advance. These types of network are able to self-discover features, correlations, rules, or clusters in the input data. The learning of unsupervised networks is dependent on the internal structure of the data, without the need for
any external guidance. Unsupervised networks are best for clustering and data compression (visualization) tasks. The Kohonen self-organizing map (SOM) is considered as the most powerful and commonly used algorithm.

Based on training type, learning rules can be divided to four general categories, as shown by Figure 1A.4. Networks associated with each rule are also shown in Figure 1A.4.

*Figure 1A.4.* Four general categories of the neural network learning rules.
6.3.5 Network Architecture

Network architecture (topology) is an important aspect of successful network design. A neural network can be defined by its topology, which specifies the number of interconnections, the strength of these interconnections, and the type of connection.

There are many different types of ANN structures (fully-connected, acyclic, feed-forward, etc), each possessing a unique purpose and procedure. Neurons are usually arranged in layers, where each layer is responsible for performing a certain task. The feed-forward architecture is the most commonly used type in both the supervised and un-supervised networks.

6.3.6 Advantages and Disadvantages of ANNs

Artificial neural networks are powerful tools for solving practical problems in the petroleum industry (Al-Fattah and Startzman, 2003; Mohagelgh, 2005). There are many advantages of neural networks techniques over conventional techniques (Patterson, 1996). The following is a summary of the major advantages of ANNs over conventional computer algorithms.

1) ANNs provide a functional use of knowledge based on experience. Because of their non-linear nature, ANNs are capable of performing functions beyond the capability of optimal linear or conventional rule-based processing techniques. Sometimes the rules are too difficult to derive or there are too many to deal with. An appropriate ANN has the ability to determine relevant rules, in a relatively short time, by its own process of self-organisation to yield the best discriminators. ANNs are sensitive to statistical regularities in large data sets, so they can derive knowledge from real relationships implicit in the data. Dueto
their adaptive nature they can adapt to changes and learn the characteristics of input signals in real-time.

2) ANNs have distributed processing and memory elements in parallel hardware realisations. This allows them to be both fault tolerant and to increase the speed of computation. If some of the processing elements are destroyed, the system will continue to function with only a minimal reduction in overall performance. The parallel structure allows a very fast computation of final results.

3) ANNs require minimal programming and algorithmic development.

4) ANNs are noise and error tolerant. They also:

- Generate non-linear relationships between inputs and outputs.
- Do not require any prior knowledge/assumption about the data distribution, or statistics.

- Provide a powerful computation tool due to their parallel structure.
- Have a strong capability for:
  (a) Function approximation
  (b) Learning and generalization
  (c) Adaptation of synaptic weights.

Meanwhile, the major disadvantages of ANNs over conventional computer algorithms are as follows.

1) ANNs generally have no design theory or unique solution.

2) ANNs cannot generally be guaranteed to converge to their global minimum, or even to converge at all. Like other adaptive systems, there is a trade off between the speed of convergence and stability.

3) ANNs can be too slow for practical use in very large scale problems when realised in digital computer simulations.
4) Other drawbacks include:

- A lack of analytical guidance for the many design parameters.
- The difficulty in understanding the theoretical analysis, due to the high connectivity and distributed non-linearity.
- The difficulty with visualising the learning process due to the use of hidden neurons.
- A lack of insight into the modelled phenomenon
- The possibility of getting trapped in local minima.
## APPENDIX 1.B

### Summary Table for Different Neural Networks

<table>
<thead>
<tr>
<th></th>
<th>Features / Advantages</th>
<th>Disadvantages</th>
<th>Applications</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>MADALINE, 1960-62 (Widrow)</td>
<td>Multiple adaptive linear elements. Have been in commercial use for over 20 years.</td>
<td>Multiple adaptive linear elements. Have been in commercial use for over 20 years.</td>
</tr>
<tr>
<td>3</td>
<td>AVALANCHE, 1967 (Grossberg)</td>
<td>Is a class of networks, no single network can do all the tasks.</td>
<td>Requires a literal playback of motor sequences. There is no simple way to alter speed or interpolate movements.</td>
</tr>
<tr>
<td>4</td>
<td>CEREBELLATION, 1969 (Marr, Albus &amp; Pellionez)</td>
<td>Similar to avalanche network. Can blend several command sequences with different weights to interpolate motions smoothly as needed.</td>
<td>Requires complicated control input.</td>
</tr>
<tr>
<td>5</td>
<td>MULTI-LAYER PERCEPTRON (BACKPROPAGATION-OF-ERROR), 1974-85 (Werbos, Parker, Rumelhart)</td>
<td>Most popular network. Works well generally. Simple to learn.</td>
<td>Supervised training only. Abundant correct input/output examples needed. Slow to train. May converge to inferior solution or not at all.</td>
</tr>
<tr>
<td>6</td>
<td>BRAIN STATE IN A BOX, 1977 (Anderson)</td>
<td>Similar to bi-directional associative memory in completing fragmented inputs.</td>
<td>one-shot decision making, no iterative reasoning.</td>
</tr>
</tbody>
</table>

Table 1B.1. Summary table for different neural networks.
| 8  | ADAPTIVE RESONANCE THEORY (ART), 1978-86 (Carpenter & Grossberg) | Very sophisticated. | Sensitive to translation, distortion and changes in scale. | Pattern recognition, especially complicated or unfamiliar to humans, eg. radar, sonar and voiceprints. Decision making under risk. Neurobiological connections and classical conditioning. |
| 9  | SELF-ORGANISING MAP (SOM), 1980 (Kohonen) | More effective than many algorithmic techniques for numerical aerodynamic flow calculations. | Requires extensive training. | Maps one geometric region onto another, eg. rectangle to aircraft. |
| 10 | HOPFIELD, 1982 (Hopfield) | Can be implemented on a large scale. Normally used with binary inputs. | The weights must be set in advance. The number of patterns that can be stored and accurately recalled is severely limited. An exemplar pattern will be unstable if it shares many bits in common with another exemplar. | Retrieval of complete data or images from fragments. Olfactory processing, Signal processing. |
| 12 | BOLTZMANN/CAUCHY MACHINE, 1985-86 (Hinton, Sejnowsky & Szu) | Simple network in which noise functions are used to find a global minimum. | Boltzmann - long training time. Cauchy - generating noise in proper statistical distribution. | Pattern recognition for images, radar and sonar. Graph search and optimisation. |
| 13 | COUNTERPROPAGATION, 1986 (Hecht-Nielsen) | Functions as a self-programming look-up table. Similar to backpropagation but less powerful. | Large number of processing elements and connections are required for high accuracy for any size of problem. | Image compression, Statistical analysis, Scoring of bank loan applications. |
| 14 | PROBABILISTIC NEURAL NETWORK (PNN), 1988 (Specht) | Training is much faster than MLP and easy in one-pass. Decision surfaces are guaranteed to approach the Bayes’-optimal boundaries as the size of the training sample grows. Sparse samples can be adequate for good performance. | All training sample points must be stored and used to classify new patterns so a large memory is required and classification time can be slower than MLP for software realisation. | Pattern recognition and classification, Mapping, Direct estimation of posteriori probability density functions. |
| 15 | CEREBELLAR MODEL ARITHMETIC COMPUTER (CMAC), 1971, (Albus) | Training is much faster than MLP. Large networks can be used and trained in practical time. Practical hardware realisation using logic cell arrays. | Generalisation is not global, only local. Design care is necessary to assure a low error solution. | Real-time robotics, Pattern recognition, Signal processing, Speech processing. |

Table 1B.2. Summary table for different neural networks.
# APPENDIX 2.A

## Acquisition Parameters

<table>
<thead>
<tr>
<th>SPREAD</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Spread Type</td>
<td>3D, 10 Line Symmetric Split, 25X25 m Bins</td>
</tr>
<tr>
<td>Traces Per Record</td>
<td>1360 (10X136)</td>
</tr>
<tr>
<td>Source Density</td>
<td>200 VP's Per Km (Square)</td>
</tr>
<tr>
<td>Line Spacing</td>
<td>Source 50 m, Receiver 200 m</td>
</tr>
<tr>
<td>Group Interval</td>
<td>Source 200 m, Receiver 50 m,</td>
</tr>
<tr>
<td>Roll</td>
<td>In-Line 1 Group Per 2 VP's, Crossline 1 Line Per Swath</td>
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<td>Depth Point Fold</td>
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</table>

<table>
<thead>
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<th>RECORDING INSTRUMENTS</th>
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<tr>
<td>Type</td>
<td>Vision</td>
</tr>
<tr>
<td>Format</td>
<td>SEG-D Demultiplexed</td>
</tr>
<tr>
<td>Sample Interval</td>
<td>2 ms</td>
</tr>
<tr>
<td>Recording Length</td>
<td>5120 ms</td>
</tr>
<tr>
<td>High Cut Filter</td>
<td>206 Hz</td>
</tr>
<tr>
<td>Gain Constant (K-gain)</td>
<td>48 db</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>VIBRATOR DATA</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Source Type</td>
<td>Vibroseis</td>
</tr>
<tr>
<td>Number of Vibrators per Sweep</td>
<td>5</td>
</tr>
<tr>
<td>Geometry of Pattern</td>
<td>In-Line</td>
</tr>
<tr>
<td>Distance Between Vibrators</td>
<td>11.26 m</td>
</tr>
<tr>
<td>Sweep Type</td>
<td>8-80 Hz Linear Up-sweep</td>
</tr>
<tr>
<td>Sweep Length</td>
<td>24000 ms</td>
</tr>
<tr>
<td>Sweep Start and End Taper Lengths</td>
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<tr>
<td>Sweeps Per Pattern</td>
<td>1</td>
</tr>
<tr>
<td>Control</td>
<td>Ground Force</td>
</tr>
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</table>

<table>
<thead>
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<th>GEOPHONE DATA</th>
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<tbody>
<tr>
<td>Receiver Type</td>
<td>SM-4 LD</td>
</tr>
<tr>
<td>Geophone String Configuration</td>
<td>12 Geophones in Series</td>
</tr>
<tr>
<td>Number of Strings Per Pattern</td>
<td>6 Connected in Parallel</td>
</tr>
<tr>
<td>Geometry of Pattern</td>
<td>Rectangle</td>
</tr>
<tr>
<td>Geophone Spacing</td>
<td>In-Line 8.33 m, Crossline 8.33 m</td>
</tr>
<tr>
<td>Geophone Row Spacing</td>
<td>In-Line 4.17 m, Crossline 4.17 m</td>
</tr>
</tbody>
</table>

Table 2A.1. Acquisition parameters summary sheet.
APPENDIX 2.B

Complex Trace and Seismic Attributes Calculations

The complex trace is a powerful tool which facilitates the derivation of seismic attributes (Robertson and Nogami, 1984; Barnes, 2007). Instantaneous amplitude, instantaneous phase, and instantaneous frequency are major attributes that can be computed from a complex trace. Hilbert transform is used for analyzing and calculating these attributes. The complex trace consists of two parts: real and imaginary. The mathematical definitions are listed below:

- The real seismic trace = \( x(t) = a(t)\cos\phi(t) \), ……………………. (2.B1)
- The imaginary seismic trace = \( y(t) = a(t)\sin\phi(t) \), ………………. (2.B2)
- The complex trace = \( z(t) = a(t)\cos\phi(t) + ia(t)\sin\phi(t) \), …… (2.6)

\( a(t) \) and \( \phi(t) \) are the instantaneous amplitude and instantaneous phase respectively. The \( a(t) \) is also called ‘reflection strength’.

\[
a(t) = (x^2(t) + y^2(t))^{1/2} = a(t)e^{i\phi(t)} , \quad \text{…………………. (2.B3)}
\]

\[
\phi(t) = \tan^{-1}\left(\frac{x^2(t)}{y^2(t)}\right) , \quad \text{……………………………. (2.B4)}
\]

The instantaneous frequency =

\[
w(t) = \frac{d\phi(t)}{dt} = \frac{d}{dt}\tan^{-1}\left[\frac{x^2(t)}{y^2(t)}\right] \quad \text{…………………………….. (2.4)}
\]

It is assumed that the real trace is defined for \(-\infty < x(t) < \infty\), then
It can be represented by the Fourier formula:

\[ f(t) = \int_{-\infty}^{\infty} B(w)e^{i\omega t} dw = \int_{0}^{\infty} C(w)\cos[\omega t + \phi(w)]dw, \quad \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots (2.5) \]

Where \( C(w) = 2|B(w)| \) and \( \phi(w) = \text{arg}(B(w)), \quad \omega > 0. \) Then

\[ f'(t) = \int_{0}^{\infty} C(w)\sin[\omega t + \phi(w)]dw, \quad \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots (2.6) \]

The complex trace is calculated by Fourier transforming the real trace, then zeroing the amplitude for negative frequencies and doubling the amplitude for positive frequencies, and then inverse Fourier transforming. The imaginary part of a complex is calculated from Hilbert transform.
APPENDIX 2.C

3-D Images of the Calculated Complex Trace at Well Locations

A01 Complex trace (3D-image)

The rest of the trace

The zone of interest (ZOI)

A03

A09
Dr. ALMOQBEL, A.

Sep 14, 2011

A15 Complex trace (3D-image)

The rest of the trace
The zone of interest (ZOI)

Seismic trace

Time (ms)

5000
0
5000
-5000
0
-5000
500
1000
1500
2000

A17

A18
A20 Complex trace (3D-image)

Quadrature trace

Seismic trace

Time (ms)

The rest of the trace

The zone of interest (ZOI)

A21
APPENDIX 3.A
The Synthetic Seismograms at Well Locations

<table>
<thead>
<tr>
<th>Well</th>
<th>Synthetic Seismogram</th>
<th>Percent</th>
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<tbody>
<tr>
<td>A01</td>
<td><img src="image" alt="A01 Seismogram" /></td>
<td>76%</td>
</tr>
<tr>
<td>A03</td>
<td><img src="image" alt="A03 Seismogram" /></td>
<td>64%</td>
</tr>
<tr>
<td>A09</td>
<td><img src="image" alt="A09 Seismogram" /></td>
<td>69%</td>
</tr>
<tr>
<td>A15</td>
<td><img src="image" alt="A15 Seismogram" /></td>
<td>78%</td>
</tr>
<tr>
<td>A17</td>
<td><img src="image" alt="A17 Seismogram" /></td>
<td>35%</td>
</tr>
<tr>
<td>A18</td>
<td><img src="image" alt="A18 Seismogram" /></td>
<td>79%</td>
</tr>
<tr>
<td>A20</td>
<td><img src="image" alt="A20 Seismogram" /></td>
<td>46%</td>
</tr>
<tr>
<td>A21</td>
<td><img src="image" alt="A21 Seismogram" /></td>
<td>79%</td>
</tr>
</tbody>
</table>
APPENDIX 3.B

The Amplitude Spectrum at Well Locations
APPENDIX 4.A

Regional Mapping of $V_p$ the Different Reservoir Levels
APPENDIX 4.B
Regional Mapping of $V_s$ the Different Reservoir Levels
APPENDIX 4.C
Regional Mapping of $\rho$ (Density) the Different Reservoir Levels
APPENDIX 4.D
Regional Mapping of \( \frac{V_p}{V_s} \) the Different Reservoir Levels
APPENDIX 4.E

Regional Mapping of $\sigma$ (Poisson Ratio) the Different Reservoir Levels
APPENDIX 7.A
WEIGHTS UPDATE AND ACTIVATION FUNCTION

7A.1 Updating the Output-Layer Weights

The general error for the input vector can be defined as:

\[ \varepsilon_k = (d_k - y_k) \]  

(7.A1)

where \( d_k \) is the desired output, and \( y_k \) is the actual output. Since the network consists of multiple units in a layer, the error in a single output unit can be defined as:

\[ \delta_{pk} = (y_{pk} - o_{pk}) \]  

(7.A2)

where

\( p \) subscript refers to the \(^p\)th training vector, and
\( k \) subscript refers to the \(^k\)th output unit.

Accordingly,

\( y_{pk} = \) desired output value from the \(^k\)th unit;
\( o_{pk} = \) actual output value from the \(^k\)th unit.

The error function for a particular input \( x_p \) that is minimized by the GDR is the sum of the squares of the errors for all output units. It has the following form:

\[ E_p = \frac{1}{2} \sum_{k=1}^{M} \delta_{pk}^2 \]  

(7.A3)

\( M \) is the number of output units. To determine the direction in which to change the weights, the negative of the gradient of \( E_p \) and \( \nabla E_p \), with respect to the weights \( w_{kj} \), should be calculated.

\[ E_p = \frac{1}{2} \sum_k (y_{pk} - o_{pk})^2 \]  

(7.A4)
From Equation (7.4) and the definition of \( \delta_{pk} \) (Equation 7.3), each component of \( \nabla E_p \) can be considered separately as follows.

The gradient of the error function with respect to a weight \( w_{kj} \) is obtained by applying the chain rule:

\[
\frac{\partial E_p}{\partial w_{kj}^o} = -(y_{pk} - o_{pk}) \frac{\partial f_k^o}{\partial (NET_{pk}^o)} \frac{\partial (NET_{pk}^o)}{\partial w_{kj}^o} \tag{7.A5}
\]

\( f_k^o \), which denotes the derivative of \( f_k^o \), is calculated as follows:

\[
\frac{\partial (NET_{pk}^o)}{\partial w_{kj}^o} = \frac{\partial}{\partial w_{kj}^o} \sum_{j=1}^{L} w_{kj}^o i_{pj} + \theta_{k}^o = i_{pj} \tag{7.A6}
\]

Combining Equations (7.5) and (7.6) yields the negative gradient:

\[
-\frac{\partial E_p}{\partial w_{kj}^o} = (y_{pk} - o_{pk}) f_k^o (NET_{pk}^o) i_{pj} \tag{7.A7}
\]

The magnitude of the weight change is proportional to the negative gradient. Thus, the weights on the output layer are updated using:

\[
w_{kj}^o(t+1) = w_{kj}^o(t) + \Delta_p w_{kj}^o(t) \tag{7.A8}
\]

where

\[
\Delta_p w_{kj}^o(t) = \alpha(y_{pk} - o_{pk}) f_k^o (NET_{pk}^o) i_{pj} \tag{7.A9}
\]

The factor \( \alpha \) is called the learning rate parameter and lies in the range \( 0 < \alpha < 1 \).

\section*{7A.2 Output Function}

The output function \( f_k^o(NET_{jk}^o) \) should be differentiable, as suggested in the ‘Activation Functions’ section. This requirement eliminates the possibility of
using a linear threshold unit, since the output function for such a unit is not
differentiable at the threshold value. The output function can be selected as a
linear function, for example:

\[ f_k^o(NET_{jk}^o) = NET_{jk}^o \]  

This defines the linear output unit. Then,

\[ f_k^o = \frac{1}{o} \]

\[ w_{kj}(t + 1) = w_{kj}(t) + \eta(y_{pk} - o_{pk})i_{pj} \] 

The last equation can be used for the linear output, regardless of the functional
form of the output function \( f_k^o \).

### 7A.3 Updating the Hidden-Layer Weights

The same procedure will be followed to derive the updates to the hidden-layer
weights. The problem arises when a measure of the error of the outputs of the
hidden layer units is needed. The total error, \( E_p \), must be somehow related to
the output values on the hidden layer. To do this, we refer back to Equation
(7.A4):

\[ E_p = 1/2 \sum_k (y_{pk} - o_{pk})^2 \]  

\[ E_p = 1/2 \sum_k (y_{pk} - f_k^o(NET_{pk}^o))^2 \] 

\[ E_p = \frac{1}{2} \sum_k (y_{pk} - f_k^o(\sum_j w_{kj}^o i_{pj} + \theta_k^o))^2 \] ............ (7.A13)

Dependence of \( i_{pj} \) on the weights of the hidden layer is taken into consideration through Equations (7.7) and (7.A1). This fact can be exploited to calculate the gradient of \( E_p \) with respect to the hidden-layer weights:

\[ \frac{\partial E_p}{\partial w_{ji}^h} = \frac{1}{2} \sum_K \frac{\partial}{\partial w_{ji}^h} (y_{pk} - o_{pk})^2 \] ................. (7.A14)

Each of the factors in Equation (7.A14) can be calculated explicitly from the previous equations. The result is:

\[ \frac{\partial E_p}{\partial w_{ji}^h} = \sum_K (y_{pk} - o_{pk}) f_k^o/ (NET_{pk}^o) w_{kj}^o f_j^h/ (NET_{pj}^h) x_{pi} \] ... (7.A15)
APPENDIX 7.B

The validation step for the porosity estimation; one well is excluded at a time.
APPENDIX 7.C

The validation step for the permeability estimation; one well is excluded at a time.
APPENDIX 8.A

ADAPTIVE RESONANCE THEORY (ART)

The adaptive resonance theory is a type of artificial neural networks that was developed by Carpenter and Grossberg (1987a). There are different forms of the ART family networks including ART2. ART1, for example, is designed to cluster binary vectors, while ART2 accepts continuous-valued vectors. Both networks cluster input using unsupervised learning (Carpenter and Grossberg, 1987b). When a pattern is presented, the proper cluster unit is chosen and that cluster’s weights are adjusted, so that the cluster unit learns the pattern.

8A.1 MOTIVATION

One of the motivations in designing the ART networks is to be able to control the degree of similarity of patterns placed in the same cluster.

ART networks are stable and are characterized by plasticity, meaning that the network has the ability to learn a new pattern equally well at any stage of learning.

The construction of the ART networks requires the input data, neurons, cluster units, and a comparison unit which compares the input pattern with the weights of the cluster unit.
**8A.2 BASIC ARCHITECTURE**

ART networks have the following basic architecture: an $F_1$ layer, $F_2$ layer, and a reset mechanism.

The $F_1$ layer consists of two portions: the input portion and the interface portion. The input portion and the interface portion of the $F_1$ layer can be denoted by $F_1$ (a) and $F_1$ (b), respectively. As some processing take place in the input portion, the inference portion combines the input signals from the input portion and the $F_2$ layer. $F_1$ (b) is connected to the $F_2$ layer by bottom-up weights which are the connections between the $i^{th}$ $F_1$ unit and the $j^{th}$ $F_2$ unit; these are designated $b_{ij}$.

The competitive layer is the $F_2$ layer; the candidate to learn the input pattern is the cluster unit with the largest network input. All other $F_2$ unit activations are set to zero. The interface units combine information from the input and cluster units. Depending on the degree of similarity between the input and the top-down weight vector, this cluster unit may or may not be allowed to learn. The decision is made by the reset unit based on signals it receives from the input (a) and interface (b) portions of the $F_1$ layer. If the decision is made that the cluster unit is not allowed to learn, then it is inhibited and a new cluster unit is selected as a candidate.

It is important to discuss the operation of the ART network to understand its basic architecture. This is provided in the following section.
8A.3 BASIC OPERATION

The learning stage presents the input patterns to the network. Each input pattern presented to the network counts as a learning trial.

The activations of all units in the network are set to zero before the pattern is presented; all \( F_2 \) units are inactive.

When a pattern is presented to the network, it continues to send its input signal until the learning trial is completed.

The vigilance parameter, a user defined parameter, is an important parameter that controls the degree of similarity required for patterns to be assigned to the same cluster unit.

The reset mechanism function controls the state of each node in the \( F_2 \) layer.

The following algorithm is a general summary of the main steps in the ART:
Step 0. Initialize parameters.
Step 1. While stopping condition is false, do Steps 2-9.
   (The calculations of Step 1 are referred to as an epoch, and comprise one presentation of each training pattern.)
Step 2. For each input vector, do Steps 3-8.
   (The calculations in Step 2 constitute a ‘learning trial’; one presentation of one pattern)
Step 3. Process \( F_1 \) layer
Step 4. While reset condition is true, do Steps 5-7.
Step 5. Find a candidate unit to learn the current input pattern.

Step 6. $F_1$ (b) units combine their inputs from $F_1$ (a) and $F_2$

Step 7. Test reset condition:
- If reset is true, then the current candidate unit is rejected (inhibited); return to Step 4.
- If reset is false, then the current candidate unit is accepted for learning; proceed to Step 8.

Step 8. Learning: The learning process may involve many weight updates and/or many epochs.

Step 9. Test stopping condition.

8A.4 LEARNING

The changes in the activations of units and weights in the adaptive resonance theory are governed by coupled differential equations (Fausett, 1994). The resonance of the network, which gives the technique its name, is derived from the fact that once a cluster unit is selected and has been accepted for learning, the bottom-up and top-down signals are maintained for an extended period, during which time the weight changes occur.

Weight changes do not reach equilibrium during any particular learning trial and more trials are required before the network stabilizes (Carpenter and Grossberg, 1987a, 1987b).
APPENDIX 8.B

[1]- All activation functions are set to zero at the beginning of a learning trial.

[2]- A single input pattern \( S \) is presented at a time.

[3]- \( S \) is normalized in sublayer \( X \) in the \( F_1 \) layer, then suppressed against noise in sublayer \( V \).

[4]- \( S \) continues from sublayer \( V \) to units in sublayers \( U \) for re-normalization.

[5]- \( S \) is then sent to units in sublayers \( W \) and \( P \).

[5A]- Signals received from \( U \) and \( S \) by a unit in \( W \) are summed; the sent to \( X \) for normalization.

[5B]- Unit in \( P \) sums the signals from both \( U \) and \( F_2 \) layer, then send it to \( Q \) for normalization.

[5B1]- \( F_2 \) layer receives signals from \( P \) through bottom-up connections by:

\[
Y_j = b_{ij} * P_i \quad \text{for all } j \text{ in } F_2
\]

[5B2]- The candidate unit \( (Y_j) \) to learn \( S \) is chosen through winner-take-all competition; \( Y_j = \max(Y_j) \).

[5B2a]- If \( Y_j \) is a new one, \( S \) will be accepted as the exemplar in the cluster, and the updating procedure will be invoked next.

[5B2b]- If \( Y_j \) has a stored exemplar \( (Z) \) the signals of \( Z \) is then transformed through top-down connections from \( F_2 \) to sublayer \( P \) of \( F_1 \)

[5B2b1]- The similarity between \( S \) and \( Z \) is now checked by the reset mechanism; the vigilance parameter \( (0 \leq \rho \leq 1) \)
[5B2b2]- $Y_j$ will either be accepted or rejected.

[5B2b2i]- If $Y_j$ is accepted, the weights ($b_{ij}$ and $t_{ji}$) will be updated next.

[5B2b2i1]- $S$ is then learned by updating the $Y_j$ weights:

\[ t_{ji} = \alpha \cdot d \cdot u_i + \{1 + \alpha \cdot d \cdot (d-1)\} \cdot t_{ji} \]

\[ b_{ij} = \alpha \cdot d \cdot u_i + \{1 + \alpha \cdot d \cdot (d-1)\} \cdot b_{ij} \]

[5B2b2ii]- If $Y_j$ is rejected, the reset signal will be sent to $F_2$.

[6]- Steps (1 to 5) completes a learning trial.

[7]- Repeat steps (1 to 6) for all input patterns.

[8]- For ART2 network to stabilize, repeat steps (1 to 7) for a large number of times.
TERMINOLOGIES

**3-D Seismic:** A relatively new exploration technique used in the search for oil and gas underground structures. The basic premise behind seismic is the same as ultra sound technology used in the medical field. Sound from a shot hole is recorded from geophones and interpreted to give a picture of the underlying structures within the earth. 3-D has now become a common practice to redefine and identify known as well as unknown structures. Many times these structures contain traps that hold oil and gas yet to be discovered.

**Absolute Porosity:** The percentage of the total bulk volume of a rock sample that is composed of pore spaces or voids.

**Acoustic Impedance:** Interference with the passage of sound waves by objects in the path of those waves. It equals the velocity of sound in a medium multiplied by the density of the medium.

**Activation Function:** A mathematical function that a neuron uses to produce an output referring to its input value. Usually this input value has to exceed a specified threshold value that determines, if an output to other neurons should be generated.

**Adaptive Resonance Theory:** The primary intuition behind the ART model is that object identification and recognition generally occur as a result of the interaction of 'top-down' observer expectations with 'bottom-up' sensory information.

**Adder:** One of the basic elements of a neuron. An adder for summing the input signals, weighted by their respective synapses.

**Amplitude Variation with Offset:** A variation in seismic reflection amplitude with change in distance between shotpoint and receiver.

**Anisotropy:** Predictable variation of a property of a material with the direction in which it is measured, which can occur at all scales. In rocks, variation in seismic velocity measured parallel or perpendicular to bedding surfaces is a form of anisotropy (non-uniformity).
Anomaly: ------- A subsurface geological feature, esp. in the subsurface, distinguished by geological, geophysical, or geochemical means, which is different from the general surroundings and is often of potential economic value.

API: ------- The universally accepted scale adopted by the American Petroleum Institute (API) for expressing the density of liquid petroleum products. The higher the API gravity, the lighter the oil and generally considered more valuable.

Arab Formation: ------- The Arab formation is a very prolific producing formation that consists of several members deposited in a carbonate shelf environment.

Formation: ------- A geological term that describes a succession of strata similar enough to form a distinctive geological unit useful for mapping or description.

Arab-D: ------- The Arab-D reservoir, limestone with some dolostone horizons, stratigraphically comprises the D member of the Arab Formation and the upper part of the Jubaila Formation.

Architecture: ------- The arrangement of neurons and pattern of connection links between them in a neural network. It is also called ‘topology’.

Artificial Intelligence: ------- A research discipline whose aim is to make computers able to simulate human abilities, especially the ability to learn. AI is separated in e.g. neural net theory, expert systems, robotics, fuzzy control systems, game theory etc.

Artificial Neural Network: ------- A digital representation of our brains. The network is made of artificial neurons, connected by weights, which are indicative of the strengths of the connections.

Axon: ------- The part of a biological neural cell that contains the dendrites, connecting this neural cell to other cells. The incoming stimulation of a neural cell is transported from the cell's core through the axon to the outgoing connections.


Back-propagation Neural Network: ------- A feedforward type neural net. Has one input layer, one output layer and at least one hidden layer. Mainly used for pattern association.

Black System: ------- A system with completely unknown information.
**Bottom-Up Weights:** ------- One of two main connections in the ART2 network. It connects the F₁ layer to F₂ layer.

**Bright Spot:** ------- A seismic amplitude anomaly or high amplitude that can indicate the presence of hydrocarbons. Bright spots result from large changes in acoustic impedance and tuning effect, such as when a gas sand underlies a shale, but can also be caused by phenomena other than the presence of hydrocarbons, such as a change in lithology. The term is often used synonymously with hydrocarbon indicator.

**Cap Rock:** ------- See ‘seal rock’.

**Carbonate Rock (reservoir):** ------- A rock, such as limestone, dolomite, or carbonate, that consists chiefly of carbonate minerals; a sedimentary rock composed of more than 50% by weight of carbonate minerals. Synonym: calcareous rock.

**Cell Body:** ------- The bulbous end of a neuron, containing the cell nucleus. The word ‘soma’ comes from the Greek meaning ‘body’; the soma of a neuron is often called the ‘cell body’.

**Clastic Rock (reservoir):** ------- A consolidated sedimentary rock composed principally of broken fragments that are derived from pre-existing rocks (of any origin) or from the solid products formed during chemical weathering of such rocks, and that have been transported mechanically to their places of deposition; e.g., a sandstone, conglomerate, or shale; or a limestone consisting of particles derived from a pre-existing limestone. Synonym: fragmental rock.

**Cluster Analysis:** ------- The assignment of a set of observations into subsets (called ‘clusters’) so that observations in the same cluster are similar in some sense.

**Competitive Learning:** ------- The neurons in a competitive layer distribute themselves to recognize presented input vectors. It is common in unsupervised training.

**Complex Trace Analysis:** ------- A mathematical method to determine seismic attributes, including reflection strength and instantaneous frequency, by using the Hilbert transform, a special form of the Fourier transform, and the quadrature trace, or the component of the signal that is 90 degrees out of phase.

**Complex Trace:** ------- A complex function whose parts are : real (seismic trace) and imaginary part (seismic trace shifted by 90 degrees).

**Core:** ------- Samples of subsurface rocks taken as a well is being drilled. The core allows geologists to examine the strata in proper sequence and thickness.
Cortical: ------- The cerebral cortex is a sheet of neural tissue that is outermost to the cerebrum of the mammalian brain. It plays a key role in memory, attention, perceptual awareness, thought, language, and consciousness. It is constituted of up to six horizontal layers, each of which has a different composition in terms of neurons and connectivity. The human cerebral cortex is 2–4 mm (0.08–0.16 inches) thick.

Crossline: ------- A seismic section of a 3-D cube in the strike direction.

Cross-plot: ------- A term used in log analysis for a plot of one parameter versus another, usually two different types of logs. Useful for the identification of lithology.

Cuttings: ------- Chips and small rock fragments brought to the surface by the flow of drilling mud as it is circulated and examined by geologists for oil content.

Data Calibration: ------- An essential step before analysing/interpreting the seismic data. It ensures a good tie between the seismic data and the well data.

Data Integration: ------- To incorporate different types of data, for example, seismic and well data.

Data Mining: ------- The process of exploring and analysing large quantities of data to discover meaningful patterns and rules.

Data-Driven Technique: ------- The technique which depends on the data to find common features in the data pairs by data generalization methods.

Deconvolution: ------- A data processing technique applied to seismic reflection data to improve the detection and resolution of reflected events. The process reverses the effect of linear filtering processes (convolution) that have been applied to the data by recording instruments or other processes.

Delta Rule: ------- Is based on the idea of continuously modifying the strengths of the connections between nodes to reduce the difference (Delta) between the desired output and the output value of a neuron.

Density: ------- Measure of concentrations of matter, expressed as mass per unit volume.

Dendrite: ------- The connections between biological neural cells. Electrical stimulation is transported from cell to cell using these connections.

Deposit: ------- An accumulation of oil, gas or other minerals which is capable of production.
**Development:** The phase in which newly discovered or proven oil or gas fields are put into production by drilling and completing production wells.

**Hydrocarbon Indicator:** Type of seismic amplitude anomaly, seismic event, or characteristic of seismic data that can occur in a hydrocarbon-bearing reservoir.

**Diagenesis:** The set of processes that cause physical and chemical changes in sediment after it has been deposited and buried under another layer of sediment. Diagenesis may culminate in lithification.

**Dim Spot:** A type of local seismic event that, in contrast to a bright spot, shows weak rather than strong amplitude. The weak amplitude might correlate with hydrocarbons that reduce the contrast in acoustic impedance between the reservoir and the overlying rock, or might be related to a stratigraphic change that reduces acoustic impedance.

**Discovery:** An exploratory well that finds hydrocarbons. See ‘exploratory well’.

**Dip-MoveOut (DMO):** The difference in the arrival times or traveltimes of a reflected wave, measured by receivers at two different offset locations, that is produced when reflectors dip. Seismic processing compensates for DMO.

**Dolomitization:** The process by which limestone is wholly or partly converted to dolomite rock or dolomitic limestone by the replacement of the original calcium carbonate (calcite) by magnesium carbonate (mineral dolomite), usually through the action of magnesium-bearing water (seawater or percolating meteoric water). It can occur penecontemporaneously or shortly after deposition of the limestone, or during lithification at a later period. Synonym: dolomization.

**Euclidean Distance:** A measure of similarity between two vectors.

**Effective Porosity:** The property of rock or soil containing intercommunicating interstices, expressed as a percent of bulk volume occupied by such interstices.

**Elastic Moduli (elastic constants):** Specify the stress-strain properties of isotropic materials in which stress is proportional to strain. They include bulk and shear moduli.

**Envelope:** The reflection strength and represent the acoustic impedance contrast.
Epoch: One complete presentation of the training set to the network during training.

**Expert System:** A system that can solve real-world problems using human knowledge and following human reasoning skills; it could replace or assist the human experts in making complex decisions by integrating all the knowledge it has in its knowledge base.

**Exploration:** Search for hydrocarbons by Geological and Geophysical (G&G) surveys that may be followed by exploration drilling.

**Exploratory Well:** A well drilled to an unexplored depth or in unproven territory, either in search of a new reservoir or to extend the known limits of a field that is already partly developed.

**Exploratory Data Analysis:** A data-driven search for statistical insights.

**F1-layer:** One of the main ART2 network layers; it is the input-processing layer.

**F2-layer:** One of the main ART2 network layers; it is the competitive (cluster) layer.

**Facies:** The characteristics of a rock mass that reflect its depositional environment. These characteristics enable the rock mass to be distinguished from rocks deposited in adjacent environments.

**Field:** A geographical area under which one or more oil or gas reservoirs lie, all of them related to the same geological structure.

**Fuzzy Logic:** A form of many-valued logic derived from fuzzy set theory to deal with reasoning that is fluid or approximate rather than fixed and exact.

**Gamma Ray:** A photon that has neither mass nor electrical charge that is emitted by the nucleus of an atom; measured in gamma logging and output from a source used in gamma-gamma logging.

**Gaussian Neighbourhood:** A bell-shape function around the winner of the competing SOM neurons.

**Generalization:** A measure of how well a network can respond to new images on which it has not been trained but which are related in some way to the training patterns. An ability to generalize is crucial to the decision making ability of the network.
**Generalized Delta Rule:** —— Minimize the 'total' of the squared errors of the output nodes.

**Genetic Algorithm:** —— A search heuristic that mimics the process of natural evolution. This heuristic is routinely used to generate useful solutions to optimization and search problems.

**Geophysicist:** —— A geophysicist applies the principles of physics to the understanding of geology.

**Geophysics:** —— The study of Earth by quantitative physical methods, especially by seismic reflection and refraction, methods.

**Geostatistical Analysis:** —— Relies on statistical model that is based on random function (or random variable) theory to model the uncertainty associated with spatial estimation and simulation.

**Ghawar Field:** —— Ghawar Field is the world’s largest and most prolific oil field, and produces 30-31° API oil from the Arab-D carbonate reservoir.

**Grey System:** —— A system of partially known and partially un-known information.

**Grey System Theory:** —— A method devised for uncertain situations, and was developed by Professor Julong Deng in China in 1982.

**Hard-data:** —— The well data (logs and core).

**Hebbian Learning:** —— One of the most common way to train a neural network; a kind of unsupervised learning; named after canadian neuropsychologist, Donald O. Hebb.

**Heterogeneous:** —— Unlike in character, quality, structure, or composition; consisting of dissimilar elements or ingredients of different kinds; not homogeneous. If the parameter depends on position.

**Hierarchical Cluster:** —— Proceeds successively by splitting large clusters, or merging smaller clusters into larger ones.

**Highstand System Tract:** —— A systems tract bounded below by a downlap surface and above by a sequence boundary, commonly abbreviated as HST. This systems tract is characterized by an aggradational to progradational parasequence set.
Highstand Deposits: ------ Consist of a thick wedge of fine-grained, skeletal and non-skeletal sands and carbonate muds derived predominantly from the platform and deposited on slopes of 25-28 °.

Hilbert Transform: ------ A linear operator which takes a function, \( u(t) \), and produces a function, \( H(u)(t) \), with the same domain. It is a basic tool in Fourier analysis, and provides a concrete means for realizing the conjugate of a given function or Fourier series.

Homogeneous: ------ Made up of similar parts or elements; of the same composition or structure throughout; uniform. Opposite of heterogeneous.

Horizon: ------ A specific sedimentary layer in a cross section of land, especially one in which a petroleum reservoir is found.

Hybrid Approach: ------ An approach that has two kinds or more of components that produce the results.

Hydrocarbon Anomalies: ------ An economical subsurface geological feature.

Hydrocarbon: ------ A chemical compound consisting only of the elements: carbon and hydrogen. Hydrocarbons, which are combustible, are the main components of fossil fuels, which include petroleum, coal and natural gas.

‘if-then’ Rule: ------ A fuzzy rule defined by a conditional statement.

Imaginary Part: ------ That part of a periodic signal that is 90 degrees out of phase with a reference signal.

Inline: ------ A seismic section of a 3-D cube in the dip direction.

Input Layer: ------ The first layer of a neural net, that accepts certain input patterns and generates output values to the weight matrix.

Instantaneous Amplitude: ------ The magnitude of the reflection. It represents the envelope of the seismic trace.

Instantaneous Attributes: ------ The main attributes calculated from complex trace analysis.

Instantaneous Frequency: ------ The times of zero crossings.

Instantaneous Phase: ------ The phase angle required to rotate the trace to the maximum.
**Instantaneous:** ------- Being a concise and quantitative description of a seismic wave at any given time.

**Integrated Sonic:** ------- The vertical travel time between depth $z_1$ and depth $z_2$.

**Interpretation:** ------- Transforming geophysical measurements into subsurface structure. More general term than inversion.

**Inversion:** ------- A procedure that allows the geology to be inferred from its image measurements and a priori knowledge.

**Isotropic:** ------- A medium with properties the same in all directions.

**Jack-knife:** ------- A cross-validation method.

**Kohonen Self-organizing Map:** ------- Built of an input layer that neurons are connected with each neuron of another layer, called ‘feature map’. The feature map can be one- or two-dimensional and each of its neurons is connected to all other neurons on the map. Mainly used for classification.

**Learning Rate:** ------- A changeable value used by several learning algorithms, which effects the changing of weight values. The greater the learning rate, the more the weight values are changed. Is usually decreased during the learning process.

**Learning Rule:** ------- The algorithm used for modifying the connection strengths, or weights, in response to training patterns while training is being carried out.

**Limestone:** ------- Sedimentary rock largely consisting of calcite. On a world-wide scale, limestone reservoirs probably contain more oil and gas reserves than all other types of reservoir rock combined.

**Lithology:** ------- The macroscopic nature of the mineral content, grain size, texture and color of rocks.

**Logs:** ------- Records made from data-gathering devices lowered into the wellbore. The devices transmit signals to the surface which are then recorded on film and used to make the record describing the formation’s porosity, fluid saturation, and lithology. The filing of a log is required by the federal government if the drill site is on federal land.

**Long-term memory (LTM):** ------- The weights associated with the bottom-up and top-down connections between the two ART2 layers.
**Lowstand System Tract (LST):** ------ A systems tract overlying a sequence boundary and overlain by a transgressive surface. Characterized by a progradational to aggradational parasequence set, this systems tract commonly includes a basin-floor fan, a slope fan and a lowstand wedge. It is often abbreviated as LST.

**Lowstand Deposit:** ------ Consists of coarse skeletal sands, gravels, and boulders deposited on primary depositional slopes of 35-45 °.

**Machine Learning:** ------ The ability of a machine to improve its performance based on previous results. Neural networks are one kind of machine learning.

**Membership Functions:** ------ The characteristic function of a fuzzy set, which assigns to each element in a universal set a value between 0 and 1.

**Mud:** ------ A fluid mixture of clay, chemicals, and weighting materials suspended in fresh water, salt water, or diesel oil.

**Multi-layer Perceptron:** ------ A feedforward type neural net. Built of an input layer, at least one hidden layer and one output layer. Mainly used for pattern association.

**Multiple Linear Regression:** ------ A technique that finds relationships between different variables that have a complex (nonlinear) relationship.

**Network Input:** ------ A set of values, called ‘pattern’, that is passed to a neural net's input neuron layer. The elements of those patterns are usually binary values.

**Network Layer:** ------ One of three types: input, hidden, or output. A layer of a neural net. The different layers of a neural net are connected by weight matrices.

**Network Output:** ------ A value or a set of values (pattern), generated by the neurons of a neural net's output layer. Used to calculate the current error value of the net.

**Neuron:** ------ An element of a neural net layer.

**Network Error:** ------ A value that indicates the ‘quality’ of a neural net's learning process. Used by neural nets with supervised learning, by comparing the current output values with the desired output values of the net. The smaller the net's error is, the better the net had been trained. Usually the error is always a value greater than zero.

**Neutron-porosity:** ------ Referring to a log of porosity based on the effect of the formation on fast neutrons emitted by a source.
Numerical Analysis: -------- The study of algorithms to solve mathematical problems concerning continuous sets of values (such as the real numbers, complex numbers or vector spaces).

Oil Field: -------- A geographical area under which an oil reservoir lies.

Oil: -------- A mixture of liquid hydrocarbons of different molecular weights.

Output Layer: -------- The last layer of a neural net, that produces the output value of the net.

Over-fitting: -------- When the model is memorizing; when it is too powerful in prediction for the training set. It refers to exceeding the optimal ANN parameters.

P-wave: -------- An elastic body wave in which particles move in the direction of propagation consisting of a train of compressions and dilatations of the material (push and pull). It is the wave assumed in most seismic surveys. It is called the primary wave.

Pattern Recognition: -------- Ability to recognize a given sub pattern within a much larger pattern. Alternatively, a machine capable of pattern recognition can be trained to extract certain features from a set of input patterns.

Perceptron Artificial Neural Network: -------- An artificial neural network capable of simple pattern recognition and classification tasks. It is composed of three layers where signals only pass forward from nodes in the input layer to nodes in the hidden layer and finally out to the output layer. There are no connections within a layer.

Permeability: -------- The capacity of a rock or stratum to allow water or other fluids, such as oil, to pass through it.

Petroleum Engineer: -------- A term including three areas of specialization: 1) Drilling engineers specialize in the drilling, workover, and completion operations, 2) Production engineers specialize in studying a well’s characteristics and using various chemical and mechanical procedures to maximize the recovery from the well, 3) Reservoir engineers design and execute the planned development of a reservoir.

Petroleum: -------- Strictly speaking, crude oil. Also used to refer to all hydrocarbons, including oil, natural gas, natural gas liquids, and related products.
Phase: ------- A description of the motion of periodic waves such as seismic waves. Waves that are not in phase are typically described by the angular difference between them, such as, ‘180 degrees out of phase’. Zero-phase wavelets are symmetrical in shape about zero time whereas non-zero-phase wavelets are asymmetrical. Non-zero-phase wavelets are converted to zero-phase wavelets to achieve the best resolution of the seismic data. Known (zero) phase well synthetics and vertical seismic profiles (VSPs) can be compared with local surface seismic data to determine the relative phase of the surface seismic wavelets. Such knowledge allows the surface seismic data to be ‘corrected’ to zero phase. The units of phase are degrees.

Physical Attributes: ------- The seismic measurements that directly relate to wave-propagation, lithology and other physical parameters.

Placticity: ------- The ability of a network to learn a new pattern.

Play: ------- Prospects within a ‘play’ have the same central geologic characteristics for example in terms of age and reservoir type.

Polarity: ------- If the signal arises from a reflection that indicates an increase in acoustic impedance, the polarity is, by convention, positive and is displayed as a peak. If the signal arises from a reflection that indicates a decrease in acoustic impedance, the polarity is negative and is displayed as a trough.

Porosity: ------- A measure of the number and size of the spaces between each particle in a rock. Porosity affects the amount of liquid and gases, such as natural gas and crude oil, that a given reservoir can contain.

Post-stack: ------- A seismic section consists of numerous traces with location given along the x-axis and two-way traveltime or depth along the y-axis. It is a processed seismic record that contains traces that have been added together from different records to reduce noise and improve overall data quality.

Pre-stack: ------- Seismic data records before stacking stage.

Processing Element: ------- One of the main elements of a neural network; it is also called node, unit, or neuron.

Production Well: ------- A well used to remove oil or gas from a reservoir.

Prospect: ------- A lead which has been fully evaluated and is ready to drill.

Prototype: ------- See ‘synapse’.

Quadrature Trace: ------- The imaginary trace which is 90 degrees phase shifted of the seismic trace.
Relative Amplitude Preserving: --------- A processing scheme that preserves the amplitude to maximize the detection of hydrocarbons.

Real Part: --------- The same as ‘seismic trace’.

Reef: --------- A buildup of limestone formed by skeletal remains of marine organisms. It often makes an excellent reservoir for petroleum.

Reflection Coefficient: --------- The ratio of amplitude of the reflected wave to the incident wave, or how much energy is reflected.

Regression: --------- A technique that finds relationships between two variables that have a complex (nonlinear) relationship.

Relative Acoustic Impedance: --------- Unlike the model-based acoustic impedance, relative acoustic impedance does not rely on an initial model.

Reservoir Characterization: --------- The continuing process of integrating and interpreting geological, geophysical, petrophysical, fluid and performance data to form a unified, consistent description of a reservoir.

Reservoir Rock: --------- A subsurface, porous, permeable rock formation in which oil and gas are found.

Resetting System: --------- One component of the ART2 neural network architecture that is responsible for accepting or rejecting the input pattern for a new cluster.

Resonate: --------- Continually comparing patterns between the two ART2 layers (F1 and F2).

S-wave: --------- Shear wave produced by shearing motion at right angles to the direction of wave propagation.

Sandstone: --------- Rock composed mainly of sand-sized particles or fragments of the mineral quartz.

Seal Rock: --------- An impervious layer of rock that overlies a reservoir rock, thus preventing hydrocarbons from escaping to the surface. Synonym: ‘cap rock’.

Seismic Attribute Analysis: --------- The use of seismic attributes to help revealing important subsurface information.

Seismic Attribute: --------- Any quantity derived from seismic data using measured time, amplitude, frequency, attenuation or any combination of these.
**Seismic Exploration:** ------ A method of prospecting for oil or gas by sending shock waves into the earth. Different rocks transmit, reflect, or refract sound waves at different speeds, so when vibrations at the surface send sound waves into the earth in all directions, they reflect to the surface at a distance and angle from the sound source that indicates the depth of the interface. These reflections are recorded and analyzed to map underground formations.

**Seismic Flattening:** ------ The hanging (flattening) of the seismic section or cube on a particular seismic event.

**Seismic Reservoir Characterization Model:** ------ A model of a reservoir that incorporates all the characteristics of the reservoir that are pertinent to its ability to store hydrocarbons and also to produce them.

**Seismic Resolution:** ------ The ability to distinguish between separate points or objects, such as sedimentary sequences in a seismic section; there is two main types of resolution: horizontal and vertical.

**Seismic Surveys:** ------ Measurements of seismic-wave travel. Seismic exploration is divided into refraction and reflection surveys, depending on whether the predominant portion of the seismic waves travel is horizontal or vertical. Refraction seismic surveys are used in exploration. Seismic reflection surveys detect boundaries between different kinds of rocks; this detection assists in mapping of geologic structures. (See also 3-D Seismic.).

**Seismic Trace:** ------ Represents the response of the elastic wavefield to velocity and density contrasts across interfaces of layers of rock or sediments as energy travels from a source through the subsurface to a receiver.

**Seismic:** ------ Data that are acquired by reflecting sound from underground strata and are processed to yield a picture of the sub-surface geology of an area.

**Shale:** ------ A type of rock composed of common clay or mud.

**Short-term memory (STM):** ------ Patterns of activity that develop over the nodes in the two ART2 layers.

**Silicon Logic Gate:** ------ Detect an input current and determine whether to produce an output current. In silicon computing, logic gates take one or more electrical inputs and provide electrical outputs based on a certain rule.

**Soft Computing:** ------ A term applied to a field within computer science which is characterized by the use of inexact solutions to computationally-hard tasks for which an exact solution cannot be derived.
**Soma:** ------ See ‘cell body’.

**Soft-data:** ------ The seismic data.

**Source Rock:** ------ Sedimentary rock, usually shale containing organic carbon in concentrations as high as 5-10% by weight.

**Stability-Plasticity Dilemma:** ------ A dilemma on, how can a system retain old memories but learn new ones.

**Stability:** ------ The ability for the new learning not to be affected by the previous learning.

**State-of-the-art:** ------ The level of development (as of procedure, process, or technique reached at any particular time usually as a result of modern methods.

**Steepest Descent Method:** ------ An extension of Laplace's method for approximating an integral, where one deforms a contour integral in the complex plane to pass near a stationary point (saddle point), in roughly the direction of steepest descent or stationary phase.

**Stratigraphy:** ------ The study of the history, composition, relative ages and distribution of strata, and the interpretation of strata to elucidate Earth history.

**Structure:** ------ Subsurface folds or fractures of strata that form a reservoir capable of holding oil or gas.

**Supervised Learning:** ------ A specific type of a learning algorithm. The output (pattern) of the net is compared with a target output (pattern). Depending on the difference between these patterns, the net error is computed.

**Support Vector Machines:** ------ A set of related supervised learning methods that analyze data and recognize patterns, used for classification and regression analysis.

**Synapse:** ------ A junction that permits a neuron to pass an electrical or chemical signal to another cell.

**Synaptic Weights:** ------ The strength or amplitude of a connection between two nodes, corresponding in biology to the amount of influence the firing of one neuron has on another.

**Synthetic Seismogram:** ------ The result of forward modeling the seismic response of an input earth model, which is defined in terms of 1-D, 2-D or 3-D variations in physical properties.
**Take-one-out**: A validation method where one set of a the data is taken out (excluded from the calculations).

**Threshold**: The amount/value that if the sum of input signals surpassed it, then a neuron sends an action potential and transmit electrical signal.

**Time Structure Map**: The map generated by picking a horizon (event) from the two-way travel time post-stack seismic data.

**Top-Down Weight**: One of two main connections in the ART2 network. It connects the F2 layer to F1 layer.

**Topography-preserving**: The topological structure mapping that preserves neighbourhood relations.

**Topology**: See ‘architecture’.

**Training Set**: A neural network is trained using a training set. A training set comprises information about the problem to be solved as input stimuli. In some computing systems the training set is called the 'facts' file.

**Transfer Function**: See ‘Activation function’.

**Transgression**: The spread or extension of the sea over land areas, and the consequent evidence of such advance (such as strata deposited unconformably on older rocks, esp. where the new marine deposits are spread far and wide over the former land surface). Also, any change (such as rise of sea level or subsidence of land) that brings offshore, typically deep-water environments to areas formerly occupied by nearshore, typically shallow-water conditions, or that shifts the boundary between marine and nonmarine deposition (or between deposition and erosion) outward from the center of a marine basin.

**Trap**: A natural configuration of layers of rock where non-porous or impermeable rocks acts as a barrier, blocking the natural upward flow of hydrocarbons.

**Trap (Stratigraphic)**: A porous section of rock surrounded by nonporous layers, holding oil or gas. They are usually very difficult to locate, although oilmen believe that most of the oil yet to be discovered will be found in these traps.

**Trap (Structural)**: A reservoir created by some cataclysmic geologic event that creates a barrier and prevents further migration. The most common structural traps are anticlines, in which at least 80 percent of the world’s oil and gas have been discovered.
Unsupervised Learning: ------ A specific type of a learning algorithm, especially for self-organizing neural nets like the Kohonen Feature Map. Unlike supervised learning, no target patterns exist.

Vigilance Parameter: ------ Produces highly detailed memories (many, fine-grained categories) when set high, while lower vigilance results in more general memories (fewer, more-general categories).

Wavelet Extraction: ------ A step in seismic processing to determine the shape of the wavelet, that would be produced by a wave train impinging upon an interface with a positive reflection coefficient.

Weight: ------ See ‘synaptic weight’.

Weight Matrix: ------ The connection structure between two neuron layers of a neural net. Its elements, the weights, are changed during the net's learning process. Each neural net has at least one weight matrix.

Well: ------ A hole bored or drilled into the earth for the purpose of obtaining water, oil or gas, or other natural resources.

Wellbore: ------ A completed well.

Wet: ------ A reservoir rock is said to be ‘wet’ when it contains water but no hydrocarbons.

White System: ------ A system of completely known information.

Wyllie's Equation: ------ Empirical time-average equation to relate the wave's phase velocity to porosity, fluid velocity, and rock matrix velocity.

Zone: ------ A specific interval of rock strata containing one or more reservoirs, used interchangeably with ‘formation’.
CURRICULUM VITAE

Abdulrahman Mohammad Al Moqbel was born in the Kingdom of Saudi Arabia. He was selected among a few in the kingdom into the Saudi Aramco College Preparation Qualification program (1991-1992). He successfully passed all requirements and tests, and then he pursued his study towards obtaining a degree of Bachelor of Science (BSc) in Geophysics. In 1995, he was granted the BSc degree in Geophysics and Geology from University of the Pacific (UOP), Stockton, California, USA. Since then, he has been working for Saudi Aramco Company, Dhahran, Saudi Arabia as a geophysicist in the Upstream Business line. He was exposed to an exciting experience working on different exploration areas within the kingdom, including: Eastern, Southern, Northwestern, and Red Sea. He has been working on exploration, new ventures, operations and development projects onshore and offshore Saudi Arabia. He has worked in different departments on different tasks such as: seismic data processor, seismic data interpreter, leads and prospects developer and evaluator, and contributed in hydrocarbon (oil and gas) assessment for reserves and resources within Saudi Arabia.

In 1998 he got the honour for winning the Vice President Award for the best paper of the year in the Exploration Department annual ceremony; the paper has been published in GeoArabia journal.

In 2002, he was granted his Master of Science degree (MSc) in Exploration Geophysics from the Department of Earth, Atmospheric and Planetary Sciences at Massachusetts Institute of Technology (MIT), Cambridge, Massachusetts, USA. Back then, his interest was focused on seismic data attributes, the inversion process for reservoir properties, and improving seismic data imaging.
His contributions in the distinguished experience of building and managing the first data room in the kingdom for the joint venture between 2004 and 2006, was recognized and rewarded by the Supreme Council for Petroleum and Minerals Affairs.

He had the chance in his next assignment to work on the assessment and packaging of Jalamid field in the Northwestern area which turned later to be one of the biggest discoveries in the Northwestern area of the kingdom.

In 2007 he enrolled in the doctoral program of the Centre for Reservoir Geophysics (CRG) at Imperial College, London (ICL), UK. Recently (in 2011), he has received his degree of Doctor of Philosophy (PhD) from the Earth Science and Engineering Department within the Royal School of Mines (RSM). His research interest was on the integration of 3-D seismic data and well logs for characterizing a carbonate reservoir and optimizing the reservoir properties using conventional and artificial intelligence approaches. He reported and presented his annual research accomplishments in both the CRG annual consortium meeting and in the EAGE conferences.

Al Moqbel is an enthusiastic, persistent, innovative proactive geoscientist with an appetite for learning. He is a member in different geological, geophysicists, and engineering societies such as AAPG, SEG, and EAGE. He has published in journals such as *GeoArabia*, and *Journal of Geophysics and Engineering*.

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